# Extracting Pædiatric Cardiovascular Information Using a Piezo-Electric Sensor

TIELMAN TERBLANCHE



*Thesis presented in partial fulfillment of the requirements for the degree of Master of Science (Engineering) at Stellenbosch University*

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# Declaration

*I, the undersigned, hereby declare that the work contained in this thesis is my own original work and that I have not previously in its entirety or in part submitted it at any university for a degree.*

SIGNATURE: ..... DATE: .....

# Abstract


## Extracting pædiatric cardiovascular information using a piezo-electric sensor

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This thesis is concerned with the development of a means of extracting cardiovascular information, such as heart rate, using a prescribed breathing monitor as source. The ability for a breathing monitor to monitor heart rate is to assist in diagnosis of certain cases of apnea which is not always detected when only monitoring breathing. An adaptive heartbeat detection system based on matched filtering is proposed which detects individual heartbeats from subjects with different physiological features. A heart rate estimation system is proposed which determines the heart rate by using the information obtained from the heartbeat detection system. Data was recorded from both adults and infants. The matched filtering heartbeat detection system was able to monitor the heart rate of adults to within less than 5% and infants within 13% of the actual heart rate as calculated using the electrocardiogram (ECG).

# Uittreksel


## Verkryging van pediatriese kardiovaskulêre inligting deur gebruik te maak van 'n piezo-electriese sensor

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In hierdie tesis word 'n metode aangebied om kardiale inligting (bv. hartkloptempo) te onttrek uit 'n voorgeskryfde asemhalingsmonitor. Die uiteindelike doel is om die asemhalingsensor die vermoë te gee om sekere gevalle van apnee te diagnoseer wat nie altyd geïdentifiseer kan word as daar van slegs asemhalingsmonitering gebruik gemaak word nie. 'n Aanpasbare hartklop waarnemingstelsel, wat gebaseer is op aangepaste filtrering, word voorgestel. Die stelsel kon hartkloppe onafhanklik waarneem uit data wat opgeneem is van verskeie vrywilligers met wisselende fisiologiese eienskappe. 'n Hartkloptempo-afskattingstelsel, wat die hartkloptempo bepaal deur gebruik te maak van die inligting afkomstig van die hartklopwaarnemingstelsel, word verder aangebied. Eksperimentele data was opgeneem van volwassenes en suigelinge. Die aangepaste filtering hartklopwaarnemingstelsel was in staat om die hartkloptempo van volwassenes korrek te bepaal binne 5 %, en die van suigelinge binne 13 %, van die werklike hartkloptempo soos bepaal deur 'n elektrokardiogram.

# Acknowledgments

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# Dedications

To my fiancée, Lauren

# Terms of Reference

The work described in this thesis was commissioned by an industrial partner, with the specific instructions to:

- Investigate whether heartbeat features are present in the signal of a given commercial piezo-electric breathing monitor.
- Evaluate a variety of possible techniques with which to reliably detect the presence of a heartbeat in the monitor's signal.
- Recommend a viable technique that could be implemented in future versions of the commercial monitor for heartbeat and heart rate detection.
- Implement a prototype system that demonstrates heartbeat and heart rate detection on recorded and synthetic signals.
- The abovementioned prototype system need not be implemented on the supplied hardware itself, but should demonstrate computer software that could potentially be incorporated in the device.

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# Nomenclature

### Variables

| | |
|---|---|
| $f$ | frequency |
| $f_s$ | sampling frequency |
| $\sigma_X^2$ | variance |

### Acronyms

| | |
|---|---|
| AAP | American Academy of Pediatrics |
| ADC | analogue to digital converter |
| ALTE | apparent life threatening event |
| AOI | apnea of infancy |
| AOP | apnea of prematurity |
| AP | action potential |
| AV | atrio-ventricular |
| BW | bandwidth |
| CHR | Committee for Human Research |
| CPU | central processing unit |
| CWT | continuous wavelet transform |
| DC | direct current |
| DCM | data collecting module |
| DFT | discrete Fourier transform |
| DWT | discrete wavelet transform |
| ECG | electrocardiography |
| FFT | fast Fourier transform |
| FT | Fourier transform |
| HMM | hidden Markov model |

HR heart rate

IDWT inverse discrete wavelet transform

LA left atrium

LV left ventrical

MCC Measurement Computing Corporation

NIH National Institute of Health

PC personal computer

PESD Piezo-electric sensor device

RA right atrium

RAM random access memory

RV right ventrical

RR respiratory rate

SA sino-atrial

SIDS sudden infant death syndrome

STFT short-time Fourier transform

USB universal serial bus

### Abbreviations

avg average

bpm beats per minute

Hz hertz (unit of frequency)

max maximum

min minimum

msec millisecond

s second

V volts

# Chapter 1

# Introduction

## 1.1 Motivation

When babies sleep, unexplained lapses in breathing, known as apnea, lead to diminished oxygen supply to the brain and heart, and can cause death. About 50 % of premature babies suffer from apnea of prematurity (AOP) and approximately 70 % of premature infants experience clinically significant apnea of infancy (AOI) events [4, 5, 6]. A prolonged apnea event in which an infant requires resuscitation is known as an apparent life-threatening event (ALTE) [7]. In a study performed by Stratton, 7.5 % of infants encountered by emergency medical services met the criteria for ALTE [8]. If intervention does not take place when such an event occurs, the infant might die.

These statistics alone illustrates the importance of monitoring babies for apneic events. Babies are often monitored continuously because the cause of apnea cannot be found, and hence monitoring is the most viable management technique. Monitoring allows the parents to reach their infant and intervene in order to terminate the apnea.

It is normal for babies to stop breathing for short periods of time (especially while sleeping), but when the duration of these episodes become longer than twenty seconds, they can become life-threatening. Apnea monitors are therefore normally set to sound an alarm if breathing ceases for more then twenty seconds. Some cases of apnea, however, might not be detected by standard apnea monitors that attempt to measure the movement of the chest in order to detect apnea. Obstructive apnea is such an example, where an airway obstruction causes air to be prevented from entering the lungs [7]. During such an event, the infant still attempts to breathe, causing the chest walls to move, but without actually receiving oxygen. Researchers have found, however, that an abrupt decrease in heart rate exists in 95 % of all apneas [9]. A secondary function of heart rate monitoring is therefore included in most apnea monitors. Due to the connection between apnea and heart rate, the ECRI Institute also states that detection of heartbeat is necessary for effective apnea monitoring.

An apnea monitor that can monitor both breathing and heart rate will therefore increase the effectiveness of the monitor in detecting apnea events.

## 1.2 Objectives

The problem addressed by this project is that of extracting cardiac information from an existing commercial breathing monitor that was prescribed for this work. This might allow for heartbeat and heart rate detection to be implemented on future versions of the monitor.

The primary objectives of the thesis can be summarized as follows:

- Investigate the presence of heartbeat in signals obtained from a prescribed breathing monitor. This monitor uses a piezo-electric vibration sensor which detects movement of the stomach in order to detect apnea events.
- Evaluate various signal processing techniques with which to reliably detect the presence of the heartbeat in the signals recorded with the monitor.
- Recommend a viable technique that could be implemented in future versions of the monitor, which would allow for the heartbeat and heart rate to be detected.
- Implement a prototype system on computer software that can demonstrate heartbeat and heart rate detection on recorded and synthetic signals.

## 1.3 Thesis outline

Chapter 2 presents a literature review covering the basic principles and facts about apnea, requirements for apnea monitors, commercial apnea monitors, the physiology of the cardiovascular system, and research related to piezo-electric sensing techniques. Methods for analysing similar signals are also discussed.

Chapter 3 describes the hardware used for this project. This includes the hardware used to record the data as well as the hardware and software used to analyse the data. The procedure of recording is also briefly explained.

In Chapter 4, the recorded data is analysed and its composition and frequency content is discussed. A brief overview is given of the methods studied in order to find the best approach in order to extract cardiovascular information from the recorded data.

The final system design is explained in detail in Chapter 5. This includes visual and numerical explanations of the processing techniques. It is shown in this chapter how matched-filtering was used to statistically determine heartbeat spread and heart rate.

Chapter 6 provides a summary and discussion of the results obtained for the methods and techniques presented in Chapter 5.

The report concludes in Chapter 7, which provides a final overview of the whole project. Some recommendations are made regarding the best approaches for future work.

# Chapter 2

# Background investigation

## 2.1 Apnea

The word "apnea" means the absence of breathing. It is normal for breathing to stop for short periods of time, but when these episodes become more frequent with a duration of more than twenty seconds, they can become life-threatening [10, 7].

Apnea of infancy (AOI) is defined as an episode of cessation of respiration for more than twenty seconds, or a shorter respiratory pause associated with a rapid decrease in heart rate resulting in bradycardia.[1] Other symptoms also include cyanosis,[2] pallor,[3] and hypotonia.[4] AOI refers to apnea events of full-term babies, i.e. infants that have a gestational age of more than 37 weeks (weeks of pregnancy at time of birth) [12, 13, 14].

In premature babies, the part of the central nervous system responsible for respiration is often not developed well enough yet to allow for breathing to take place continuously [4]. Apnea of prematurity (AOP) is defined as a cessation of breathing for more than twenty seconds, or a cessation of less than twenty seconds but accompanied by bradycardia. Premature babies are babies born with a gestational age of 37 weeks or less [13] (literature varies with the age ranging form 34 to 37 weeks). AOP is fairly common among premature infants and about 50% of premature babies have AOP [4, 5, 6]. Approximately 70% of premature infants experience clinically significant AOI events and apnea is more frequent in less mature infants [6].

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[1] Bradycardia is defined as a heart rate that is slower than normal [2, p. 378].

[2] Cyanosis is defined as the bluish colouration of the skin due to the presence of deoxygenated blood near the surface of the skin [2, p. 113].

[3] Pallor is defined as a lack of skin colour or paleness [11]

[4] Hypotonia is defined as the condition when a person has a deficient muscle tone [11].

Although there have been cases where apnea occurred while the infant was awake [15], it appears to be more common while the baby is sleeping [5].

Babies that experience an event of apnea either start breathing on their own again, or require help to resume breathing. When an event of apnea occurs, stimulating the baby by rubbing its skin or gently patting the child can assist the baby to resume normal breathing [5]. If gentle stimulation does not work, sometimes a more vigorous stimulation may be required which includes tapping the baby's hands or feet, or even pinching. The official medical term for a prolonged apnea event which did not claim the infant's life is referred to as an apparent life-threatening event (ALTE) [7]. The age ranges for ALTEs shows a peak incidence between one week and two months [16].

### 2.1.1 Types of apnea

There are three different types of apneas, defined by the cause of the event:

- Central or diaphragmatic apnea – This is the type of apnea where the baby makes no effort to breathe, the infant's chest stands still and no air passes through the mouth or nose [7]. Central apnea generally happens due to a disturbance in the brain's respiratory control centre [5]. In premature infants, central apnea results due to an immature development of the respiratory control centre [4].

- Obstructive apnea – During obstructive apnea the chest of the infant moves, but no air passes through the mouth or nose. This is usually due to soft tissue (such as the tongue) obstructing the upper airway [7].

- Mixed apnea – This form of apnea occurs when an infant experiences a combination of the above-mentioned factors during a single event [7].

The different types of apnea require different detection methods in order to successfully detect and monitor them. During obstructive apnea, for example, the infant has an obstructed upper airway and is unable to breathe, but still tries to breathe, causing the chest or stomach to continue to move as if breathing. Therefore, monitors that only rely on the chest or stomach movement for breath detection will have difficulty detecting obstructive sleep apnea. Simpson also stated that because respiration monitors detect absence of breathing movements and not necessarily cessation of respiratory airflow, they will not indicate obstructive apnea [17]. The device used in this project relies on breathing movement caused by the stomach and therefore also needs to measure another physiological function in order to successfully detect obstructive sleep apnea. Since an apneic episode is often accompanied by a decrease in heart rate, heart rate is the function that the majority of apnea monitors

measure. The ECRI Institute also states in a medical device safety report [18] that detection of the heartbeat is necessary for effective monitoring, as apneas are often accompanied by decreases in heart rate.

From a study done to determine the characteristics that cause bradycardia during sleep apnea [9], researchers found that bradycardia occurred during 95% of all apneas. It was found that, as the duration of apneas increased, the slowing in heart rate also increased, i.e. longer-lasting apnea resulted in bradycardia with a greater drop in the heart rate. An evaluation of a large number of patients experiencing apneic episodes showed that the most common abnormality in cardiac rhythm is bradycardia [19]. It is believed that the probable cause for increased sudden infant death is this bradycardia which occurs in both infants and adults [20, 19]. Bradycardia in infants is defined as a heart rate less than 80 beats per minute (bpm) [15]. Apnea monitors are therefore normally set to alarm when breathing stops for more than twenty seconds or when the heart rate decreases to less than 80 bpm [7].

A separate study showed, however, that bradycardia can also exist without apnea [21]. Recordings were made with a threshold set to a heart rate of less than 60 bpm for more than 5 seconds (extreme threshold) or less then 80 bpm for at least fifteen seconds (conventional threshold). This is equivalent to customary practice [21]. This research showed that 41% of recorded events exceeded the conventional threshold, and 10% exceeded the extreme threshold. Apnea without bradycardia occurred in 75% of events exceeding the conventional threshold, while bradycardia without apnea occurred in 14% of events exceeding the conventional threshold. Therefore, it seems that monitoring of both respiration and the heart rate is important.

### 2.1.2 Defining sudden infant death syndrome

Sudden infant death syndrome (SIDS) has been defined as "the sudden death of an infant under one year of age that remains unexplained after a thorough case investigation, including performance of a complete autopsy, examination of the death scene, and review of the clinical history" [22]. SIDS usually occurs in infants between one month and one year of age and SIDS accounts for approximately two deaths per 1000 live births in the United States [14]. SIDS remains the leading cause of infant deaths during the first year of life after the neonatal period [14, 23]. SIDS numbers peak at two to three months of age, then falls rapidly. Ninety percent of SIDS occurs before six months [22].

Schwartz states that most cases of SIDS most likely result from a neural control defect of either cardiac functions or respiratory functions that may trigger a lethal sequence of events [24].

### 2.1.3 Relation between apnea and SIDS

Premature infants often unexpectedly cease to breathe , and in many instances the infant may not resume breathing without intervention. Because premature infants do not always struggle in an attempt to resume breathing, the hypothesis stating that apnea is a cause of SIDS seems attractive. This situation appears to be present in many cases of SIDS [6]. However, this theory of the relation between SIDS and apnea has to date not yet been established. Furthermore, most infants who die of SIDS are full-term infants who, according to parental reports, apparently had no events of apnea prior to death [6]. According to Shoemaker [25], no association links the increased incidence of apnea and bradycardia in preterm infants with SIDS. He also states that apnea of prematurity has not been shown to be a precursor to SIDS and is not a proven risk factor for SIDS. The American Academy of Pediatrics (AAP) also acknowledges that no established relationship (predictive or precursor) exists between prolonged apnea and SIDS and that apnea of prematurity is not a risk factor for SIDS [12]. Prolonged apnea has, however, been reported in infants with near-miss SIDS (infants who have had an ALTE). The National Institute of Child Health and Human Development SIDS Cooperative Epidemiologic Study was a case-control study consisting of 757 definite or probable cases of SIDS and 1514 control infants. The investigation found no links or associations between AOP and SIDS and stated that the relationship with post-neonatal apnea was arguable [21].

Because of the lack of association links, Shoemaker advises that home apnea monitoring for the purpose of SIDS prevention cannot be recommended [25]. However, a report released by the National Institute of Health (NIH) states that despite the lack of scientific proof, the NIH accepts that cardio-respiratory monitoring may be beneficial for infants declared to be "high risk" [12].

### 2.1.4 Apnea impact on the family

A monitor often helps to relieve the parents from the anxiety of taking a formally sick baby away from the hospital, although parents having a child on a monitor is often associated with heightened levels of anxiety independent on whether the infant was at home or hospitalized [26].

A study conducted on the psychological effects of home apnea monitoring to determine emotional distress and family functioning [27]. It was found that all experienced increased stress in the post-partum period. But the study also showed that parents of monitored infants had an increased incidence of subjective depression and hostility at two weeks post-partum compared to parents of unmonitored infants. However, a one-year follow-up revealed that the majority of the parents who consistently used the monitor stated that they felt more

secure using the monitor and believed that it was helpful.

## 2.2 Devices used for apnea monitoring

The introduction of apnea monitors took place in the mid 1960s for the purpose of managing apnea of prematurity in hospital settings [13]. The primary function of an apnea monitor is to sound an alarm upon the cessation of breathing, while other secondary parameters might also be monitored (of which the heart rate is the most important) [28]. An apnea monitor can, however, not cure apnea.

This section gives a brief overview of commercial apnea monitors and briefly discusses their disadvantages. Some requirements for apnea monitors are also presented.

### 2.2.1 Requirements for an apnea monitor

The ECRI Institute's Medical Device Safety Report stated that a built-in heart monitor is a requirement for an apnea monitor and described this feature as a critical safety feature [18]. During a device evaluation, the FDA suggested that apnea monitors should include both a primary means of detection (e.g. respiration) as well as a secondary means of detection (e.g. heart rate) [28]. Some hospitals also state that continuous monitoring is suggested for respiration as well as heart rate because a respiratory monitor alone might miss obstructive apnea [29].

Another important consideration for apnea monitors is its power requirements. Apnea monitors are electrical instruments which require power to function and will therefore be inoperable during power failures. There is no risk to the infant in this case other than the fact that the infant might suffer a case of apnea that will go unnoticed. The requirement for power also restricts the use of a monitor to a house or building where electricity is available. There are, however, some models that can use batteries as backup during power failures [30, 31].

It is advised that parents do not travel long distances alone in a car with an infant for it would be impossible to constantly monitor the baby while driving [15]. Also, evidence indicates that there is an increased risk of adverse cardiorespiratory effects for pre-term infants when placed in a semi-upright position, like in a child car seat [32]. Except for the problem of having to stop suddenly when an event has been detected and intervention is required, having a monitor that is battery operated can ensure that the infant is continuously monitored.

### 2.2.2 Types of monitors

#### Mattress

There are monitors that make use of passive sensor pads located underneath the mattress of a baby's cot [33]. This type of monitor detects the baby's breathing to determine whether it becomes abnormally slow, or if the motion (and consequently breathing) has stopped. Normal breathing patterns are indicated by a flashing green light which gives peace of mind to the caretaker. If the baby stops breathing for 20 seconds or if the breathing rate drops below 10 breaths a minute, a loud alarm is sounded.

#### Cardio monitor

A cardio monitor is a sensor system that detects the heartbeat of a patient. The most common way of monitoring the heart is by using an electrocardiograph (ECG). These monitors are sometimes used as apnea monitors because bradycardia is present in most cases of apnea. Monitoring the heart rate only is not advisable since many apneas exist without the presence of bradycardia [21].

#### Respiratory monitor

A respiratory monitor monitors the breathing efforts of a patient. This method was originally the most commonly used method to detect apnea since apnea is the cessation of breathing. Since research, however, showed that not all apneas can be detected by only monitoring breathing, more advanced monitors were developed that have secondary functions that are more sensitive towards apnea detection.

#### Cardiorespiratory monitor

The cardiorespiratory monitor,[5] is a device that shows a constant readout of breathing, heart rhythm, and heart rate. This device is connected by three wires (leads) to the stomach, arm or leg, and chest, with each wire resting on the skin and held in place by a small round adhesive patch. The cardiorespiratory monitor sounds an alarm when the heart rate or respiratory rate falls outside a safe level [34].

[5] Also known as a heart rate monitor or apnea monitor [34].

#### Infant home apnea monitors

Home apnea monitors are portable cardiorespiratory machines that can monitor respiration and heart rate of an infant at home. Limits can be set on this machine for the heart and breathing rate of an infant and an alarm is sounded if the rate drops below limit. These monitors are smaller and less complex than the typical monitors found at hospitals. A home apnea monitor is used for infants that are deemed well enough to go home, but still have minor problems with breathing (apnea) and heart rate drops (bradycardia). The home apnea monitor is connected to the infant either by a belt attached around the chest and stomach, or by stick-on electrodes [34].

#### Piezoelectric sensor device

The piezoelectric sensor device (PESD) is the device that was used during the execution of this project to extract cardiovascular information. The PESD was designed to monitor breathing of an infant by detecting movement of the stomach due to the infant's breathing efforts. When breathing ceases, a stimulator inside the device is activated to startle the infant, similar to the effect of someone rubbing or tapping the baby's skin when breathing ceased. If no breathing is detected even after stimulation, an alarm is sounded to arouse the attention of the caretaker.

### 2.2.3 Advantages of the PESD over other monitors

Both the cardio-based monitor as well as the respiration-based monitor therefore is excluded from the recommended apnea monitors based on the recommendations discussed in Section 2.2.1.

One of the first noticeable advantages of the PESD over the other monitors is that it requires no wires to be connected to a baby for either power or monitoring purposes. The FDA mentioned the risk of strangulation of a patient and states that a monitor should be designed or have features to minimize the risk of strangulation of the patient by wires and tubing, especially when the device is intended for infants [28]. Also, most of these monitors require that cables are connected to the infant during monitoring. Except for the small danger of strangulation, the connection of cables and stick-on electrodes to an infant while sleeping might also contribute to discomfort due to skin irritation [34, 15, 32]. Another problem with using stick-on electrodes is that the monitor leads sometimes detach, which can cause the alarm to sound [35]. It has also been reported that the attachment of electrodes on the infants are problematic for many parents [15].

When an infant is required to use a home apnea monitor, it should be connected to the

infant whenever they are not under constant surveillance. It is also required that a parent be in constant hearing range of the apnea monitor alarm, because if the parent delays for more than ten seconds, irreversible damage may occur and resuscitation may be required [15]. There have been cases where apnea occurred while the infant was awake and also where infants fall asleep quickly and without warning [15]. A child could unexpectedly fall asleep (away from a apnea monitor) and have an apneic episode without the parents' knowledge. There is thus a need for a monitor that is completely mobile. Owing to the fact that the device used during this project is small, battery-operated and fully portable, allows for it to be kept nearby at all times to be connected to the infant whenever and wherever he/she may fall asleep.

During an apneic episode, the infant will very often respond to outside stimuli such as a mild flick on the fingers or feet. The PESD has a built-in vibrating stimulator that is activated when apnea is detected.

### 2.2.4 When monitoring can be stopped

Apnea usually disappears naturally as the infant matures [4]. Monitoring is usually stopped when an infant has had no observable apnea events for approximately two months [15]. There is evidence to suggest that if monitoring is required for infants, it can usually be discontinued after 43 weeks post-menstrual age [36]. By using a monitor with event recording, it can help to determine when it is safe for monitoring to be discontinued.

## 2.3 Other piezo-electric related research

Piezoelectric sensors have a wide range of use in the biomedical world and assists in measuring and monitoring patients, as well as in the diagnosis of certain pathologies.

### 2.3.1 The use of piezoelectric sensors in other biomedical applications

Some of the uses of piezoelectric sensors include the detection of force, position (linear and rotary) and vibration or acceleration [37]. The following is a list of some of the uses for a piezoelectric sensor as described by Measurement Specialities [37]:

1. Piezoelectric film can be used as a contact microphone in an electric stethoscope to listen to heartbeat and breathing sounds. These contact microphones are often used to sense snoring in patients suffering from sleep apnea.

2. Piezoelectric film can be used to detect inhalation for oxygen conservers which opens an oxygen flow valve.

3. In some pacemakers, a piezoelectric film sensor is used as an activity monitor (vibration sensor) to detect the movement of a patient so that an increased blood flow can be triggered by increasing the heart rate.

4. Piezoelectric film has also been used as an ultrasound transducer to measure bone density.

5. Some bedside vital sign monitors contain piezoelectric sensors to measure respiration and heart rate in patients.

6. For patients suffering from sleep apnea, piezoelectric film can be used as a dynamic strain gauge to sense chest movement.

### 2.3.2 Previous research on cardiovascular data extraction using a piezo-electric sensor

Research was done by Mack *et al.* [38] using an ultra-sensitive piezoelectric transducer to record pulse and respiration data. The sensor is used together with an air-filled bladder to pick up the signal. Eleven subjects were used for the tests. Recordings were done at two locations to obtain the pulse and respiration data. During the first tests, the vibration sensor was placed underneath the subject's calf while they were lying on their back. The second position for recording was with the vibration sensor placed underneath the subject's chest while lying on their stomach. A pulse oximeter was used to evaluate the recorded pulse data while the subjects were asked to count their breaths in order to evaluate the respiratory data.

Signal conditioning techniques such as a low pass anti-aliasing filter, an instrumentation amplifier, band pass filters, and non-inverting amplifiers were used to record the desired signal. The results showed that the pulse data was within $\pm$ 5 % of the pulse oximeter's heart rate reading. The recorded respiration data corresponded exactly to the number of counted breaths. The tests were done with heart rates ranging from 49 to 84 bpm.

Two locations were chosen to selectively record the desired data. The first position was underneath the calf which has no breathing artefacts. The second was underneath the chest where breathing is the most prominent source (movement of the chest is predominantly due to breathing). In this thesis, however, the sensor location is to be at one specific location only so that the original functionality of the device can be maintained. The two signals (breathing and heartbeat) are to be separated using only this one location. Problems associated with

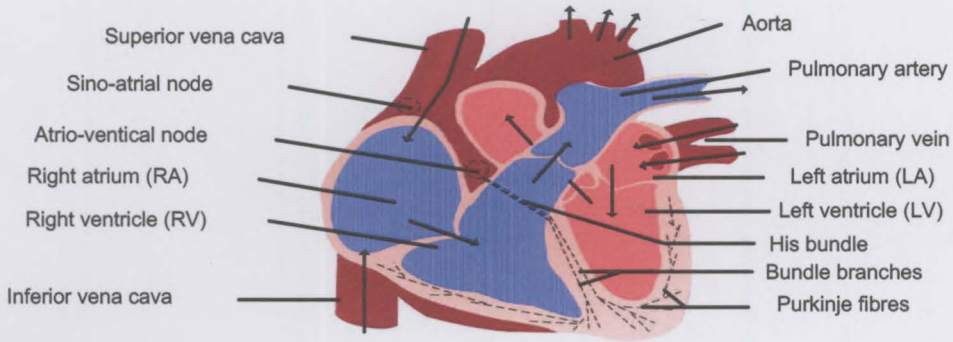


**Figure 2.1:** *Anatomy of the heart [2].*

the separation of the two signals from this one source will be discussed in more detail in Section 4.1.

To the author's knowledge, no further work has been done to date in the detection of cardiovascular information using a piezoelectric sensor.

## 2.4 Understanding the heart

### 2.4.1 The physiological working of the heart [1, 2]

The heart is a muscular pump responsible for pumping blood through the body. The heart consists of four chambers, the left atrium (LA), right atrium (RA), left ventricle (LV) and right ventricle (RV) (See Figure 2.1). The right atrium receives the deoxygenated blood from the body and pumps it into the right ventricle, which pumps the blood into the lungs where it becomes oxygenated. From there, the oxygenated blood is pumped into the left atrium down into the left ventricle and via the aorta to the rest of the body. The two ventricles are the largest chambers in the heart with thick muscular walls. The left ventricle perform the strongest as well as the most important pumping action of the heart as it is responsible for the pumping of the oxygenated blood to the rest of the body and pumps against the pressure of the rest of the vascular system of the body. The filling stage of the heart cycle is known as diastole and the contracting or pumping phase of the cycle is known as systole.

The contraction of the heart is controlled by the conducting system of the heart. Electrical impulses are distributed along the heart walls by means of a network of specialized cardiac muscle cells known as nodal cells and conducting cells. Nodal cells establish the rate of cardiac contraction whereas conducting cells distributes this stimulates to the myocardium.

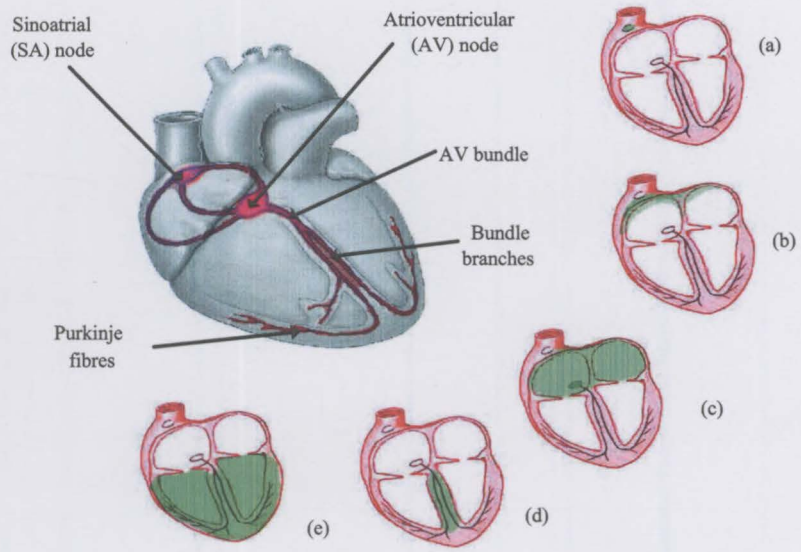


**Figure 2.2:** *Anatomy of the electrical system of the heart is shown top left. Plots (a)–(e) illustrates the events that takes place to cause a heart contraction (heart beat) [2].*

### 2.4.2 The electrical system of the heart

An electrical impulse in the body that results from the mechanical contraction of a single cell when stimulated by an electrical current, is known as an action potential (AP) [39]. The sino-atrial (SA) node is the natural pacemaker of the heart and generates its own action potentials. These action potentials propagate through the rest of the heart causing excitation and contraction. The cardiac cycle takes place through the following sequence of events, as illustrated in Figure 2.2 [2]:

1. The SA node gets activated at time (plot (a)).
2. The impulse spreads across the atrium walls and reaches the atrio-ventricular (AV) node (plot (b)). This step takes 50 ms to complete.
3. There is a 100 ms delay at the AV node during which atrial contraction is initiated (plot (c)).
4. The impulse then travels from the AV node to the Purkinje fibres via the interventricular septum (plot (d)). The elapsed time is 175 ms.
5. The Purkinje fibres distribute the impulse throughout the ventricular myocardium.

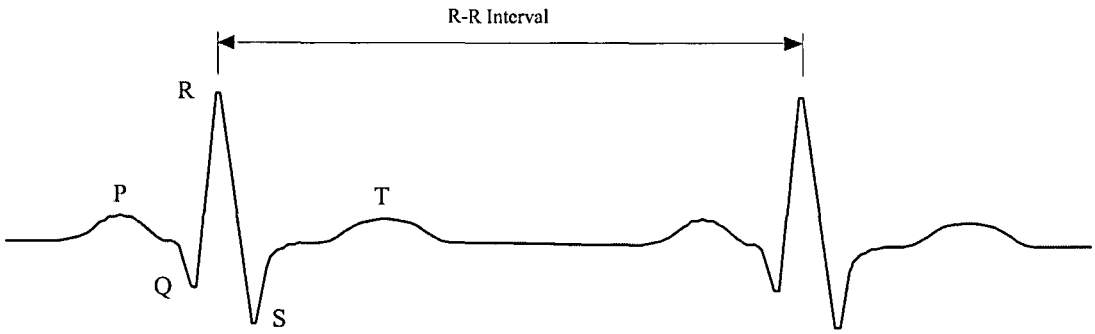


**Figure 2.3:** *An electrocardiogram for one of the standard configurations. The R-R interval can be used to determine the heart rate.*

Atrial contraction is now completed and ventricular contraction begins (plot (e)). The elapsed time is 225 ms.

### 2.4.3 Understanding the electrocardiogram signal

The electrical impulses and events that cause the heart to contract can be detected by strategically placed electrodes on the skin. A recording of these events is known as an electrocardiogram (ECG).

Figure 2.3 shows the ECG obtained from a standard configuration and indicates the different parts that make up the ECG. The P wave is caused by the depolarisation of the atria. Contraction of the atria begins about 100 ms after the beginning of the P wave. The QRS complex is a result of the depolarisation of the ventricles. This part of the ECG is stronger than the rest because of the larger mass of the ventricular muscle compared to that of the atria. The contraction of the ventricles takes place shortly after the R wave peak. The T wave is a result of the repolarisation of the ventricles. Repolarisation of the atria takes place at the same time the ventricles depolarise and therefore masked by the QRS complex. The R-R interval of the ECG can be used to determine the heart rate [40].

## 2.5 Signal processing techniques

This section documents the signal processing techniques that were studied during the execution of this project in order to find a means of reliably detecting and monitoring the heart rate from the signals captured with the PESD.

### 2.5.1 Fourier Transform

The Fourier transform (FT) is used to decompose a continuous aperiodic time-domain signal into component sinusoids of different frequencies. Fourier analysis transforms a time-based view of a signal into a frequency-based view. The Fourier coefficients are indicative of the frequency content of a signal and are calculated by:

$$X(f) = \int_{-\infty}^{\infty} x(t)e^{-2j\pi ft}dt \tag{2.1}$$

The time-domain signal $x(t)$ can completely be recovered from the Fourier transform using the inverse Fourier transform (IFT):

$$x(t) = \frac{1}{2\pi}\int_{-\infty}^{\infty} X(f)e^{2j\pi ft}df \tag{2.2}$$

In digital signal applications, continuous signals are first sampled by an analogue-to-digital converter (ADC) and then transferred to a computer for further analysis. The FT however applies only to continuous signals of time, so modified FT equations are required that is compatible with digital samples of a continuous signal. The discrete Fourier transform (DFT) of $x(k)$ is given by:

$$X(m) = \sum_{k=0}^{N-1} x(k)e^{-j\frac{2\pi mk}{N}}; \quad m = 0, 1, \ldots, N/2 \tag{2.3}$$

and provides the means to represent digital signals in the frequency domain. The digital frequency index is represented by index $m$, $N$ represents the number of samples, $x(k)$ is the sampled approximation of $x(t)$, and k is the discrete time variable. The inverse discrete Fourier transform (IDFT) is then given by:

$$x(k) = \frac{1}{N}\sum_{m=0}^{N-1} X(m)e^{j\frac{2\pi mk}{N}}; \quad k = 0, 1, \ldots, N-1 \tag{2.4}$$

and allows for the reconstruction of the digital time-domain signal. The fast Fourier transform (FFT) is a computationally efficient implementation of the DFT.

The frequency information is of interest since different actions in the body produces different frequencies of pressure waves (vibrations). By studying the frequency components of signals, it is often possible to distinguish between different sources and isolate them. One disadvantage of Fourier analysis is that temporal information in the analysed signal is lost [40]. When examining a Fourier transform, it is impossible to tell when a particular event took place or when specific frequencies occurred because it integrates the observation over the total observation time [41]. Most biological signals contain numerous non-stationary[6] characteristics with time-dependant spectral content. These characteristics are often the most useful, and Fourier analysis is not well-suited to detect them.

[6] A signal where the statistical properties change over time

### 2.5.2 Short-time Fourier transform and spectrograms

To help preserve the time-domain information, the short-time Fourier transform (STFT) was developed [40]. The STFT is a commonly used method for studying non-stationary signals [42, p. 93].

The STFT is implemented by performing the FT on small windows within a signal. A signal is subdivided into small windows by a process called windowing. During windowing, a signal is multiplied by a short-duration time window centred around the specific time of interest. The FT is then applied on this window before the next window is taken at the next time instance. The window is subsequently slid along the time axis of the signal until the whole signal has been covered. This then gives an estimate of the frequency content of a signal at each time instance by mapping the signal in a 2D function of time and frequency. This produces a time-frequency distribution of the signal known, as a spectrogram. The STFT is described mathematically by:

$$X(\omega,\tau) = \int_{-\infty}^{\infty} x(t)w(t-\tau)e^{-j\omega t}\,dt \tag{2.5}$$

where $w(t)$ is the window function whose centre is slide to time $\tau$, x(t) is the signal to be transformed and $\omega$ is the angular frequency. The inverse of the STFT is given by

$$x(t) = \frac{1}{2\pi}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} X(\omega,\tau)w(t-\tau)e^{j\omega t}\,d\omega\,d\tau \tag{2.6}$$

The STFT represents a compromise between time and frequency-based views. The STFT provides some information about when and at what frequencies an event occurred. However, this information can only be obtained with limited precision which is dependent on the size of the window. Throughout an analysis the time window stays the same for all frequencies, and is therefore not sensitive to changes in the time-domain [43, 40]. This disadvantage has led to the development of other techniques that better describe the time-varying nature of a signal.

### 2.5.3 Wavelets

Wavelet analysis is different from FT and STFT in that the signals to be analysed no longer need to be stationary and the windows are no longer fixed in length. In wavelet analysis, signals are broken up into shifted and scaled versions of the original "mother" wavelet. The smaller the scale factor, the more "compressed" the wavelet, whereas the higher scales correspond to more "stretched" wavelets. Wavelet analysis allows the use of long time intervals where more precise low-frequency information is required, and shorter regions where high-frequency information is desired.

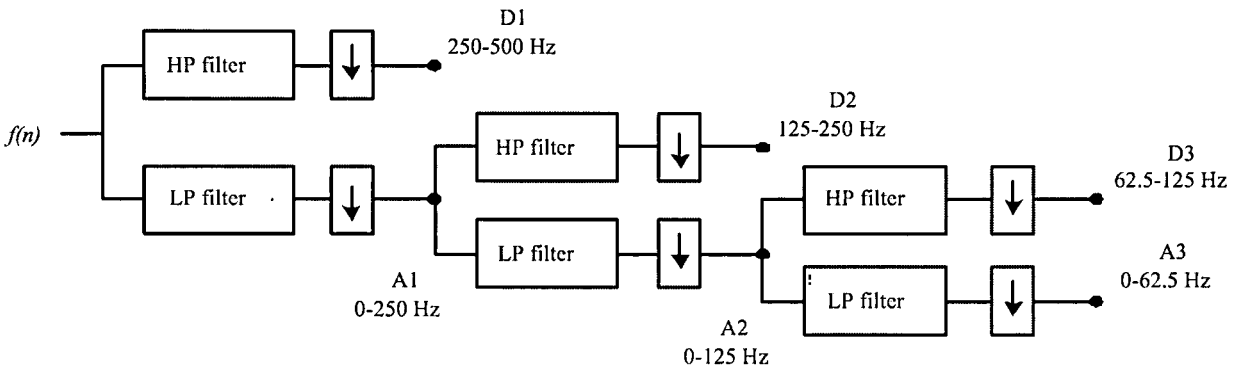


**Figure 2.4:** *Graphical presentation of wavelet decomposition for a 1 kHz signal.*

The original mother wavelet is selected and stepped through the signal at every time instance of interest and integrated to yield wavelet coefficients. The scale of the wavelet is then changed (stretched or compressed) and the new wavelet is stepped through the signal, multiplied and integrated to yield wavelet coefficients. The stretched or compressed versions of the mother wavelet are often referred to as scales (higher scales and lower scales consecutively). This process is then repeated for the set of scales that has been chosen. This process produces wavelet coefficients that are a function of scale and position. The relative size of a coefficient is an indication of the presence of a component in the signal that is similar to the wavelet. Sörnmo describes a wavelet as an oscillating function whose energy is concentrated in time in order to better analyse transient, non-stationary signals [41].

At the most basic level of wavelet analysis, a signal is split into its high and low-frequency components. The low-frequency (high-scale) components are the *approximations* and the high-frequency (low-scale) components are the *details*. The decomposition process can be iterated so that one signal is broken down into many lower resolution components. Figure 2.4 shows a graphical representation of the decomposition process for a 1 kHz signal. The highest frequency present in a 1 kHz signal is 500 Hz, according to the Nyquist criterion. After the first set of filters, the approximations contains the frequency components from 0-250 Hz while the details will contain the components from 250-500 Hz. For the next breakdown level, the approximation of the previous level gets filtered to produce another approximation and detail. This process is repeated until the desired breakdown level or until the remaining samples are equal to one. When performing one such process of filtering to break down the signal, the output consists of double the amount of data. Instead of having one signal that consists of $N$ samples, there are now two, thereby increasing the number of samples to $2N$. The data is therefore downsampled after filtering by taking every second sample.

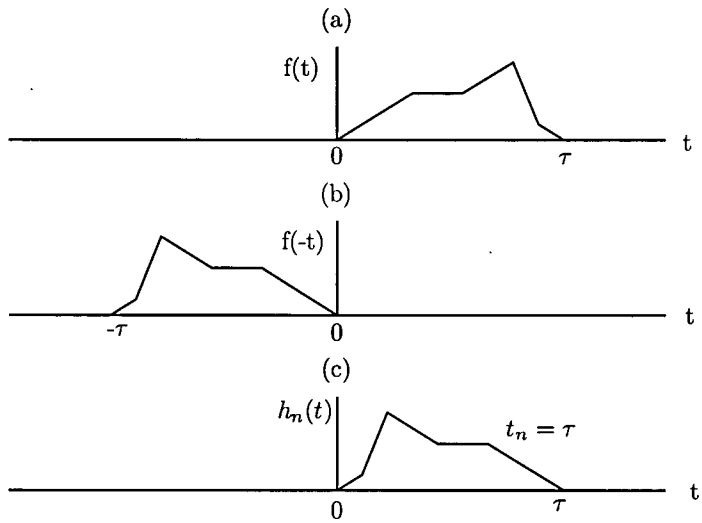


**Figure 2.5:** *Illustration of the steps taken to create the matched filter.*

### 2.5.4 Matched filtering

A matched filter is a filter which optimises a desired signal by correlating one signal, $s(t)$, with another signal, $x(t)$, in order to determine the presence of $s(t)$ in $x(t)$ [44]. A matched filter maximizes the output energy of a signal at the time instances that correspond to the known signal $s(t)$. By definition, a matched filter is equivalent to performing convolution between $x(t)$ and the time-reversed version of $s(t)$. The impulse response of a matched filter can be given by:

$$h(\tau) = ks(p - \tau), \tag{2.7}$$

where $k$ and $p$ are arbitrary constants [45]. Figure 2.5 shows an illustration of the time-reversal process. The matched filter can be used to determine the presence of a known heartbeat waveform in another signal where the location of the heartbeats are not known.

An illustration of the output from a matched filter is shown in Figure 2.6 (a). A heartbeat sequence was generated by using a single period from a sinusoidal wave as a single heartbeat. Matched filtering was then performed and the output plotted. One can see that the output remains zero where no heartbeat is present and is maximized at the positions corresponding to heartbeats. Random noise was then added to the signal and matched filtering was performed on it again. The result is shown in Figure 2.6 (b). From these two figures it can be seen how matched filtering identifies the locations of where the presence of the first signal (known wavelet) can be found in the second signal.

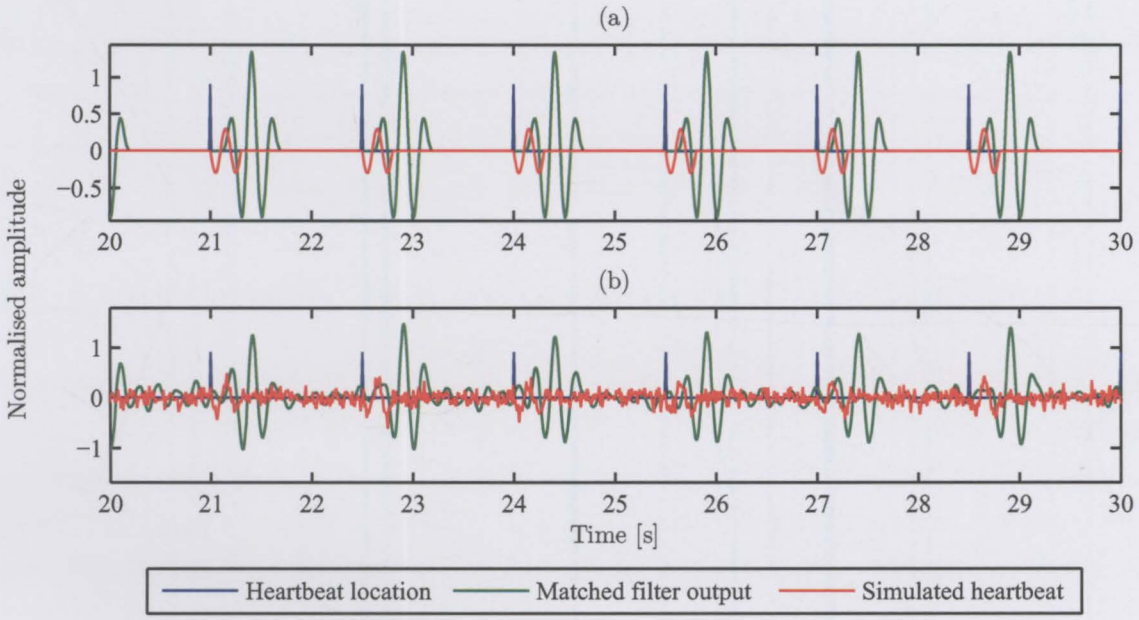


**Figure 2.6:** *Illustration of a matched filter output*

# Chapter 3

# Hardware and software

This chapter provides a detailed description of the hardware and software used during the execution of this project. The hardware consists of the piezo-electric sensor previously mentioned, an electrocardiograph (ECG), a data collecting module and two personal computers. Both the recording of data and the analysing thereof were done with Matlab.

## 3.1 Description of hardware used for recording

The purpose of this project is to attempt to extract cardiovascular information from an infant by using a prescribed device (the PESD). However, to determine the accuracy of the extracted heartbeat, a second source is required to serve as a reference to which the analysed PESD data can be compared. The ECG is the obvious preferred standard for basic cardiac monitoring and diagnosis, and was hence chosen as the reference source for heart rate detection.

The use of personal computers while recording, allows for easy synchronisation of the two data sources. To synchronise the PESD data with the ECG data, the recording of the two sources must be synchronised. The PESD, however, does not have a built-in unit which will allow it to interface with a computer directly, therefore a data collection module (DCM) was required. The data collecting module samples the data from the PESD and then translates the information to a computer on which the analysis of the data can be done.

Each of the aforementioned hardware components will now be discussed in more detail.

### 3.1.1 Piezo-electric sensor device (PESD)

As discussed in Section 2.2.2, the PESD was designed to monitor breathing of an infant by detecting movement of the stomach due to the infants breathing efforts.

The PESD is a small device (with dimensions 6 cm x 4 cm x 2.5 cm) with a design that allows for the monitor to simply clip onto the waistband of the nappy of a baby.

It has built-in memory to record event data which can be analysed in order to determine the information regarding the event. The PESD operates from a 3 V battery built into the unit and samples data through its 12-bit ADC. Detection of breathing happens through a piezo-electric sensor which is stimulated as the stomach moves up and down. Inside the clip of the PESD is an ultra-sensitive piezo-electric sensor. The sensor is separated from the stomach by a thin membrane and any movement made by the stomach is detected. The detected signal is low-pass filtered at 10 Hz and amplified. This amplified signal is then interpreted by the microcontroller's ADC and analysed to determine whether breathing is present or not.

#### Using the PESD to record data

The PESD is a totally concealed device with no external connections to the electronics. In order to record the data obtained from the piezo-electric sensor, the PESD had to be opened and a connection was made at the pin of the micro controller after the signal has been filtered and amplified. The reason recording was done after filtering and amplification is in order to capture the same signal as the microcontroller. A ground connection was also made to establish a common ground between the PESD and the DCM.

### 3.1.2 Electrocardiograph

The department where the work for this project was conducted had an ECG available for use. To keep project costs low, it was decided to use the ECG that was available. The ECG is a 3-lead ECG with a built-in ADC, but is restricted to a sampling frequency of 8 kHz. The ECG has a built-in USB interface which allows for it to be connected directly to a computer.

### 3.1.3 Data collection module

As already mentioned, a data collecting module (DCM) is needed to serve as an interface between the PESD and the computer, allowing the PESD data to be recorded and saved onto the computer. The DCM used is a PMD-1608FS analogue and digital input-output (I/O) module from Measurement Computing Corporation (MCC). The PMD-1608FS is a USB 2.0 full-speed device which offers simultaneous sampling of up to eight analogue inputs. Each input channel contains one 16-bit ADC and offers an accuracy of less then 3 mV for a range of ±5 V [46, 47]. The DCM has a built-in I/O analogue to digital converter (ADC) module which can collect data from eight different sources, and transmits it through a single

Universal Serial Bus (USB) to a computer which records the incoming data. Although only one channel is needed to record the PESD data, having more channels allowed for the possibility of recording data that originates from another location on the PESD, such as directly from the piezo sensor before filtering and amplifying. This signal was used to see the effect of the filter and amplifier in the PESD circuit by comparing the signal recorded before and after the filter and amplifier. By studying the effect of the filter and amplifier, it is possible to conclude whether it improves or complicates the aim of this project. This is, however, discussed in more detail in Section 4.1.

This particular DCM was used because it was readily available. A check was done to see if it met certain requirements, which are listed below. Both criteria mentioned below were chosen so that the recoded signal would be the same as the signal that would have been interpreted by the PESD microcontroller.

- The output voltage from the PESD (between 0 V and 3.3 V) should be within the limits of the DCM (±5 V). This ensures that the signal recorded is the same as the signal that the PESD microcontroller would have received and that no information is lost due to the ADC limiting the incoming data.

- The 16-bit ADC of the DCM is of greater resolution than the 12-bit ADC of the PESD microcontroller. As in the point above, this ensures that no information is lost due to lower sampling resolution.

Initially, sampling of data from the PESD was done using a sampling frequency of 8 kHz. This sampling frequency was chosen due to the ECG sampling restriction of 8 kHz. The choice to keep the sampling frequencies of the two sources the same was merely for convenience, since it is for example easier to plot, compare and index data that has been sampled at the same frequency and is the same length. After a study was done on the signals obtained from both sources however, it was decided to digitally downsample the data to 100 Hz using Matlab. The choice for this sampling rate will be discussed in detail in Section 4.1.5.

## 3.2 Software used for recording and analysing of data

All recording and processing of data was done using Matlab Version 7.4.0.289 (R2007a). The Matlab toolboxes used for this project are the Data Acquisition Toolbox, Fixed-Point Toolbox, Neural Network Toolbox, Signal Processing Toolbox, Symbolic Math Toolbox and the Wavelet Toolbox.

To enable Matlab to identify the DCM, its drivers were installed which was done by installing the Instacal software supplied with the DCM. For more detail on setting up the two

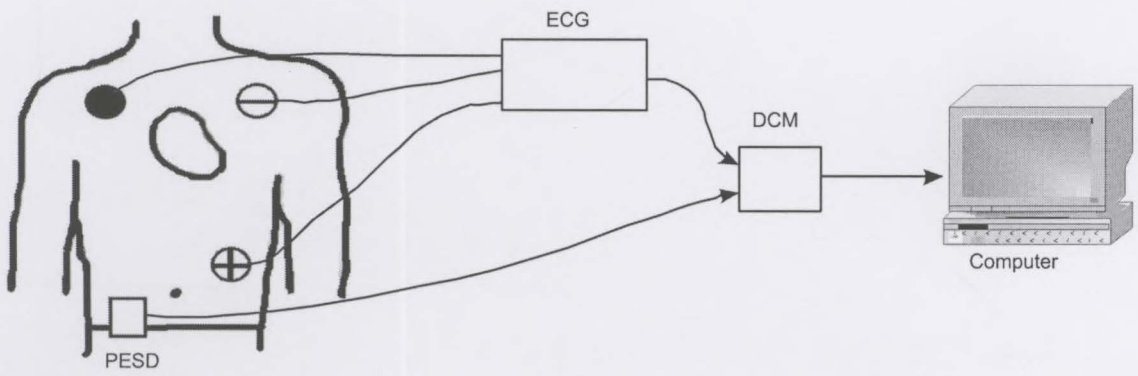


**Figure 3.1:** *Illustration of the hardware connections with PESD connected at the belt line and the ECG electrodes connected in a standard 3-lead configuration [3].*

input devices to work with Matlab, please refer to MathWorks's Data Acquisition Toolbox Quick Reference Guide [48].

## 3.3 Procedure of recording

Before recording of infant data at hospitals could take place, an ethics protocol was written and submitted for approval. Ethical committee approval was obtained. Written, informed consent was then gained from all participants in the study.

The ethical approval process was however expected to take more than two months, so initial recording of data took place on adults only. Adult data was therefore used in the initial signal processing experiments to determine which method proves most promising in detecting the heartbeat.

In order to maintain the functionality of the original device, the scope of this project is limited to recording data from the same location on a patient where the device would be connected for its originally designed use. The PESD is thus connected to the nappy (with infants) or pants (with adults) for the recording of all the data, so that the primary functionality of respiration monitoring is not altered (see Figure 3.1). The 3-lead ECG is one of the most commonly used and the configuration is shown in Figure 3.1 [3]. Both the PESD and ECG are connected to the DCM which translates the information to the computer.

The PESD was designed to record breathing while the infant is sleeping. Therefore, during the recording process the adult volunteers were asked to lie on their backs in the same way they would while sleeping. Data recordings on infants took place while they were sleeping.

# Chapter 4

# Investigation of candidate solutions

This chapter takes a look at the methods attempted in order to develop a final methodology. Before starting a design for a final methodology, experiments were conducted using different signal processing techniques in order to find a method that appears to be most promising for reaching the objective of the project. The experiments conducted were done in a simple way with only a few sets of data. The results in the following sections are not detail solutions for the different methods, but rather constitute background research. Only the method that yielded promising results early on in the experiments was to be used in the final design methodology. This chapter serves to briefly show some results achieved with various candidate solutions. Discussions are also included regarding the possible effectiveness of the methods.

## 4.1 Decomposition of the piezo-electric sensor data

A detailed study of the signals extracted from the PESD was done in order to try and identify the different sources responsible for the overall shape of the signal. The signals recorded from adults revealed more detailed compared to the data recorded from infants. For this reason, adult data was first used to study the composition of the PESD signals. Only two physiological sources could be identified that could contribute to the signal: While sleeping, only the heart beating and breathing of the lungs causes continuous movement of the body, especially at the chest and stomach area.

### 4.1.1 Composition of the extracted signal

After a study on signals recorded from adults, two clear components could be identified in the signal. The first contributes to the biggest part of the wave and has a sawtooth shape. A few volunteers were asked to count their breaths while the recording was done.

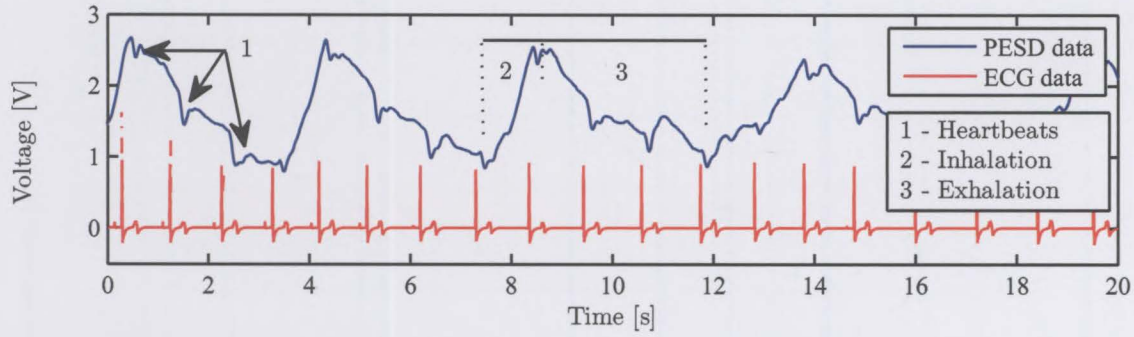


**Figure 4.1:** *Explanation of the output obtained from the PESD with the ECG as reference.*

As expected, the breaths counted corresponded perfectly to the number of sawtooth shapes present in the recorded signal. These structures were then accepted to be respiration. The small temporal structures riding on the respiration part of the wave could also be identified. These structures corresponded well to the ECG peaks and were therefore ascribed to being the heartbeat component. The source of the respiration component is due to the upward and downward motion of the abdomen of the person during inhalation and exhalation. The heartbeat component however, is due to the contracting action of the heart. When the ventricle muscles of the heart contract, the heart shrinks in volume which causes the chest to also shrink very slightly. These stomach movements caused by the heart contracting, are the cause of the heartbeat component measured by the PESD.

Figure 4.1 shows the composition of a signal recorded from an adult volunteer. The duration of the inhalation stage is short while the exhalation stage is longer. The heartbeat structures clearly correspond to the ECG peaks.

During the recording process, a very noticeable difference was seen between the data recorded from adults and that of infants. This difference can be seen in Figure 4.2 when comparing plots (a) and (b). A particularly noticeable difference between the signals obtained from the two different age groups is the presence of the small temporal heartbeat structures riding on the respiration part of the wave. These heartbeat structures are small, but clearly visible in the adult data, whereas they are almost not visible at all to the naked eye in the infant data. A possible cause for this difference is that the heart of an adult is much larger than that of an infant. Other possible factors might include relative difference in muscle mass and fat concentrations. To the author's knowledge, however, no literature is available that compares the stomach movements of adults to that of infants, or factors influencing the movement of the abdomen.

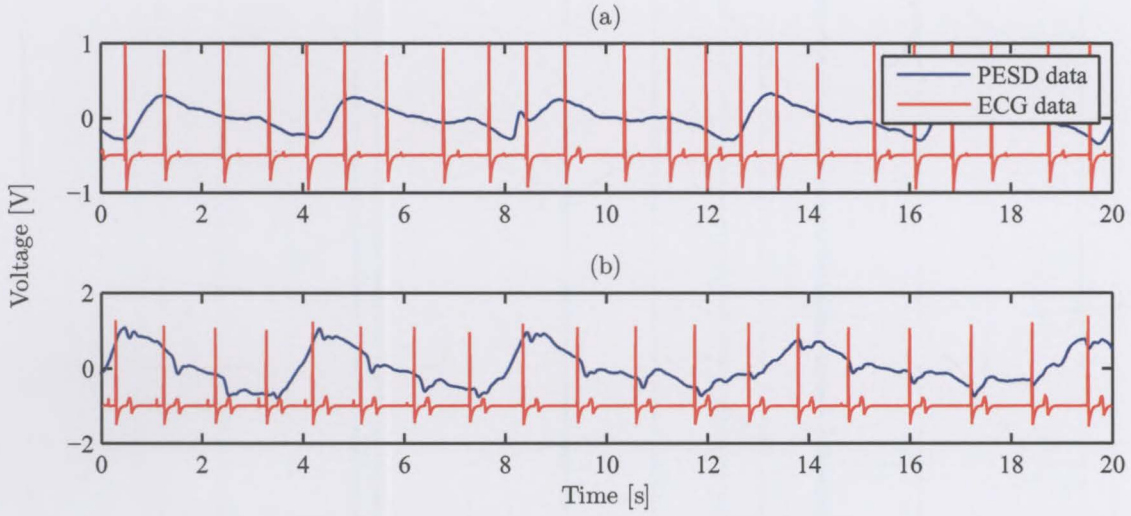


**Figure 4.2:** *Data recorded from (a) an infant and (b) and adult.*

### 4.1.2 Signal containing only cardiovascular data

During the initial recording process, recordings were made of adults and infants while they were breathing, as well as of adults holding their breath. The latter was done so that the heartbeat can be examined separately from the rest of the signal. The recording of adults holding their breath was done twice for each volunteer. The first was done with the volunteer inhaling, then holding his breath for twenty seconds (inhalation data) while the second was done with the volunteer exhaling most of the air from his lungs, and then holding his breath for twenty seconds (exhalation data). The recording time of twenty seconds was chosen as a comfortable time for a volunteer to hold his breath. A comparison was made between the inhalation and exhalation data to see what the change in lung volume does to the cardiovascular part of the recorded data.

The inhalation and exhalation data differ significantly. By looking at the plots in Figure 4.3, one can see that the exhalation data contains more higher frequency components while the inhalation data contains more lower frequency data.

This indicates that the heartbeat pulse looks different during inhalation and exhalation. This result is due to a phenomenon called pulses paradoxes. Pulses paradoxes is a variation of the heart pulse where the pulse becomes weaker during inhalation and stronger during exhalation, due to a variation in blood pressure. [49].

The difference in the composition of the cardiovascular part of the PESD signal between different people was also studied. Plot (a) in Figure 4.4 shows four different plots, each being a plot of only cardiovascular data recorded from a different volunteer. In each plot,

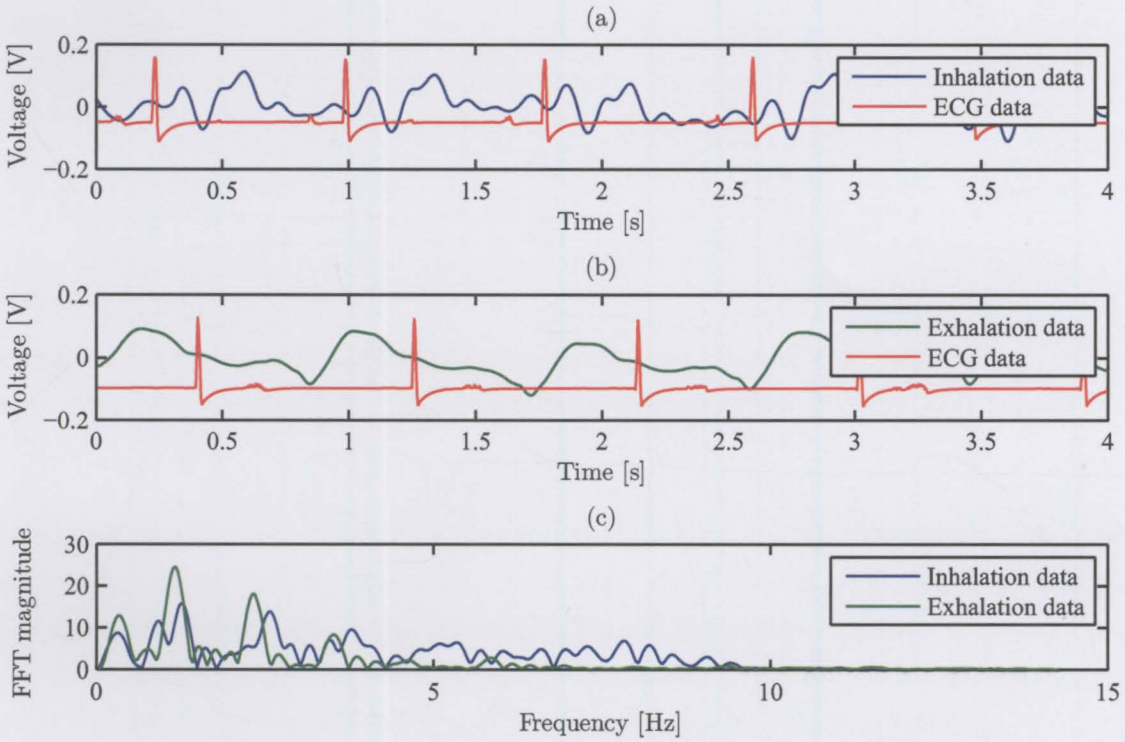


**Figure 4.3:** *Plot of (a) inhalation data, (b) exhalation data and (c) frequency spectrum of both inhalation and exhalation data.*

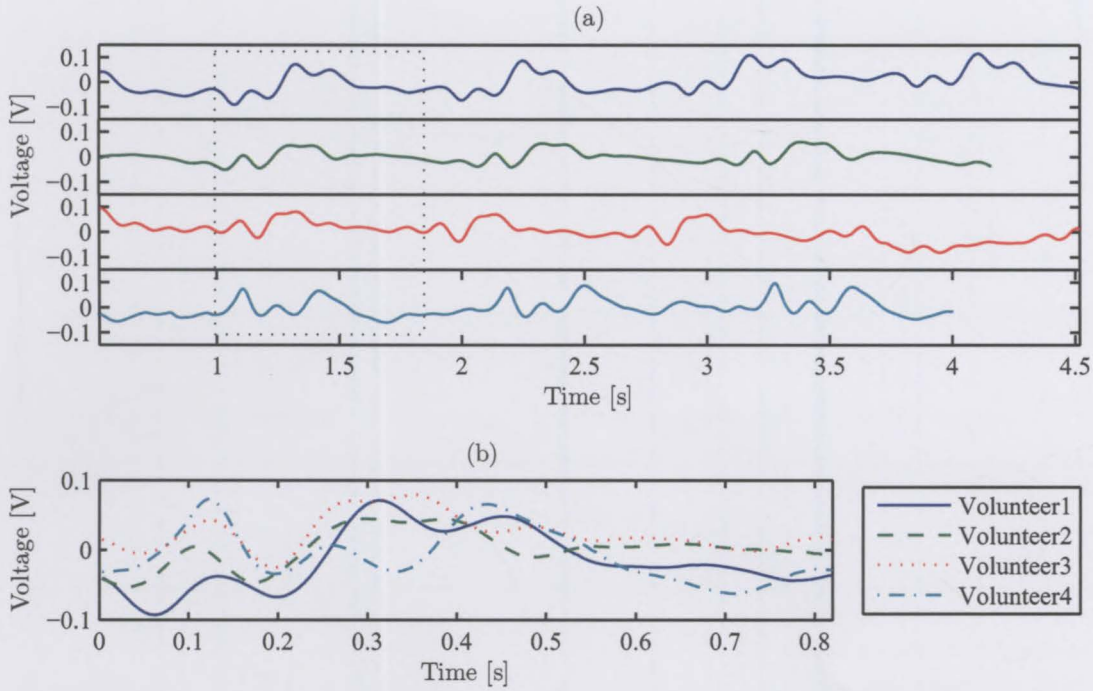


**Figure 4.4:** *Four plots revealing cardiovascular information of four different volunteers are shown in (a). Plot (b) consists of four heartbeat structures taken from each volunteer.*

the heartbeat structure is identified and encircled by a dotted rectangle. The heartbeat structures were identified by extracting that part of the signal that starts at the peak of the ECG signal (not shown in the plots). These heartbeat structures from the different volunteers are shown in plot (b). From plot (b) it can be seen how the heartbeat component in the signals from the four volunteers differ significantly in the time domain.

This study of the heartbeats revealed that a single isolated heartbeat (wavelet) might not be sufficient in attempting to isolate the heartbeat using just filtering since the heartbeats differ enormously depending on the breathing cycle, and there is a large variation among individuals.

### 4.1.3 Effect of PESD filter on extracted signal

So far the composition of the recorded data has been explained and analysed. However, the recorded data was obtained directly from the microcontroller. As mentioned in Section 3.1.1, the PESD filters and amplifies the signal obtained from the piezoelectric sensor before it enters the microcontroller. This section explores the effect of the filter in order to establish if valuable data, particularly cardiovascular data, is lost due to the filter cut-off frequency.

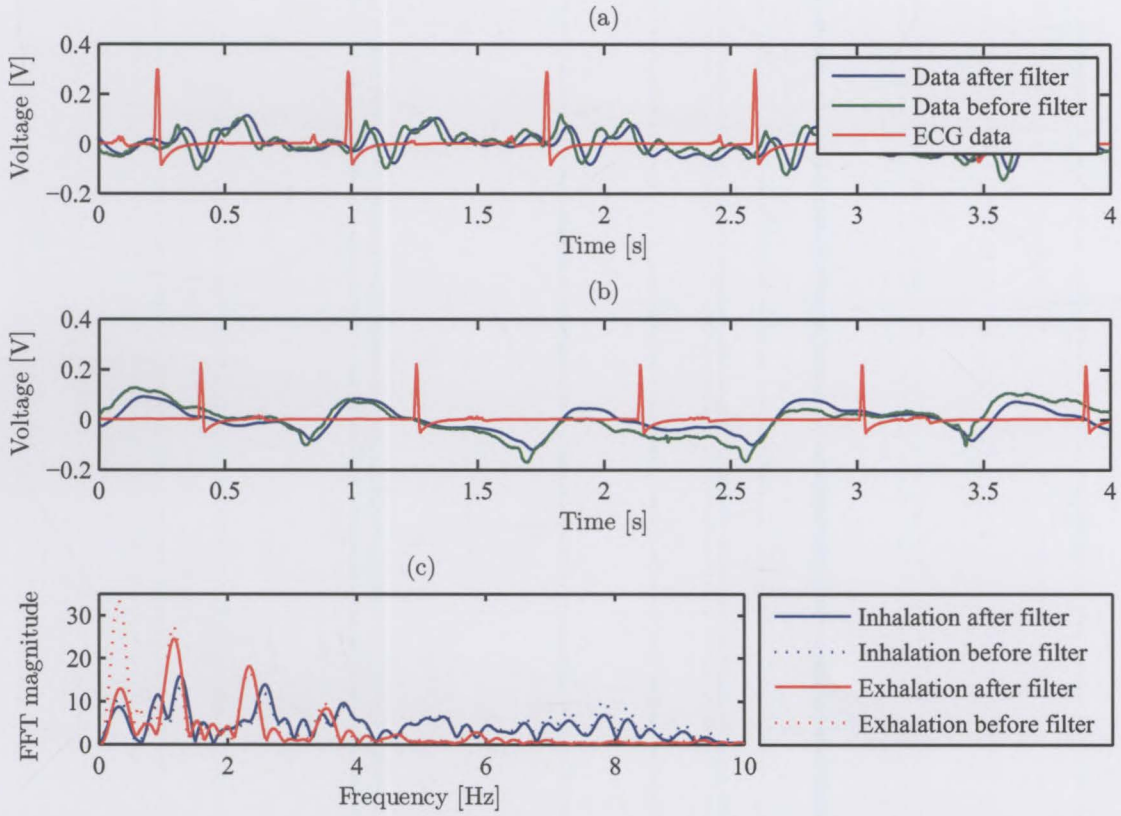


**Figure 4.5:** *Plot of (a) PESD inhalation data recorded before and after the filter and (b) PESD exhalation data recorded before and after filter. Plot (c) contains the frequency plots using the FFT of each of the four signals*

If that is the case, then recommendations can be made regarding the efficacy of the filter.

For this experiment, another connection was made inside the PESD before the filter. This is done so that data can be obtained that has not yet been changed by the filter, so that the effect of the filter can be studied. There were thus three connections made inside the PESD. The first was made after the filter, the second before the filter and the third is ground connection. A few recordings were made on adults while asking them to hold their breath after inhaling as well as after exhaling so that only cardiovascular data (inhalation and exhalation data) can be recorded. Both sets of data were then normalised to the same magnitude and the effect of the filter was studied.

The result for one of the adults is shown in Figure 4.5, but all the recorded data showed a similar result. Plot (a) in Figure 4.5 reveals that the difference between the data recorded before and after the PESD filter for inhalation data is very small. One can make the same observation for exhalation data when examining plot (b). Plot (c) confirms these two ob-

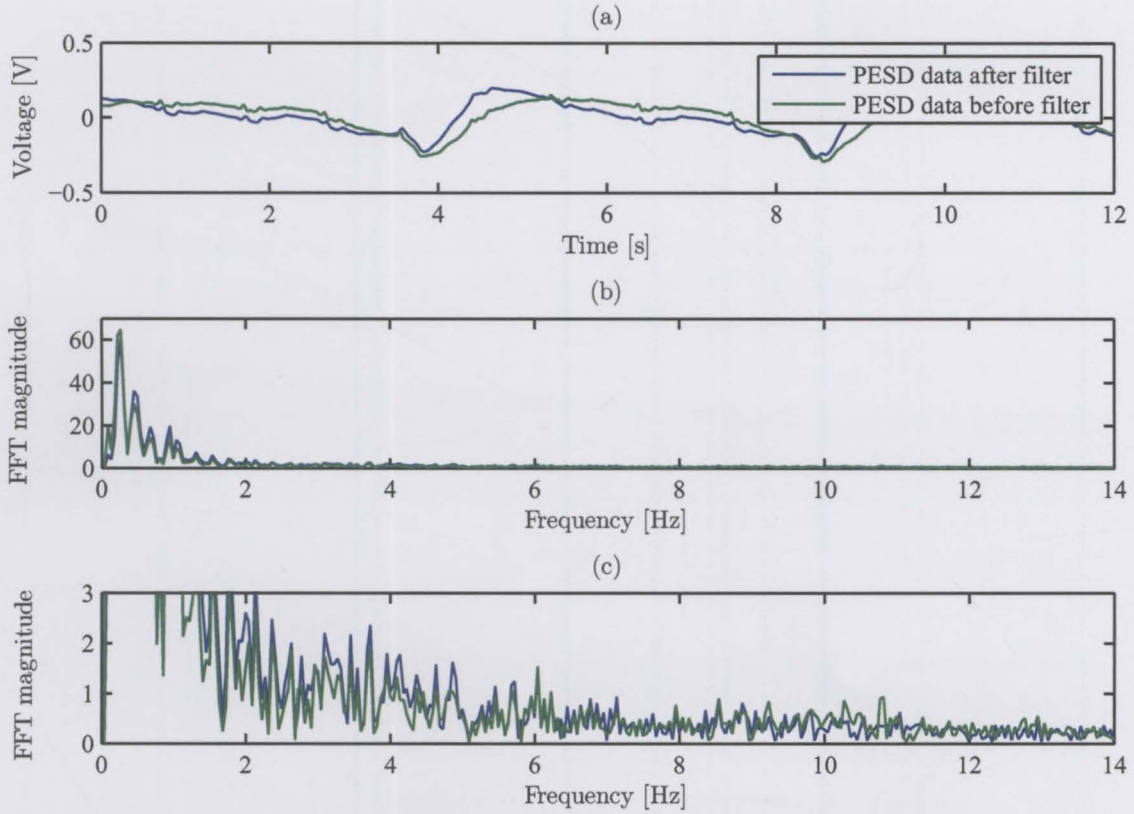


**Figure 4.6:** *Plot of (a) PESD data recorded before and after the filter (b) with a corresponding frequency plot. Plot (c) is a zoomed version of plot (b)*

servations in that the frequency components present in these two sets of signals are almost identical. Only the exhalation data shows a stronger low frequency component, but this can be ascribed to a small DC offset in the data.

The above experiment was then repeated with the volunteers breathing normally. Each volunteer was asked to lie down and breathe normally while a recording was done. Figure 4.6 shows the difference between data recorded before and after the filter. This time, a slight difference can be seen between the two signals, especially during the inhalation part of the breathing, but this is still small. The fast Fourier transform (FFT) of plot (c) once again reveals that the frequencies of the signal obtained before and after the filter is almost identical.

The above results led to the conclusion that the effect of the filter on the piezoelectric sensor data is negligible and will not negatively influence the signals. For the duration of this report, the PESD data that are used for analysis originated from after the PESD filter, with the connection made at the pin of the microcontroller.

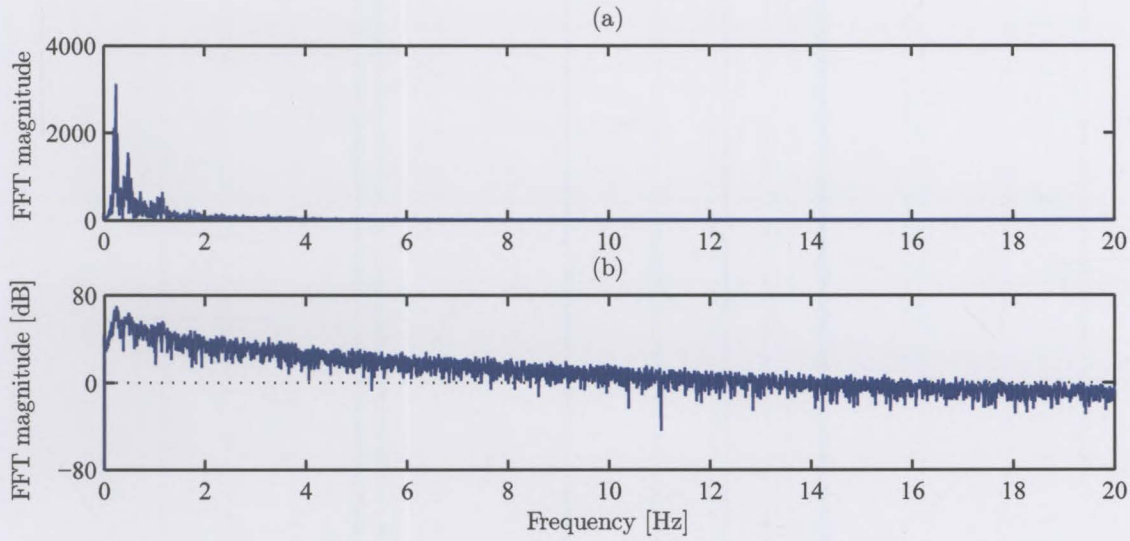


**Figure 4.7:** *Frequency plot of PESD data is shown in (a) with a logarithmic plot in (b).*

### 4.1.4 Effect of PESD amplifier on extracted signal

The amplification of the sensor signal results in the signal being significantly larger (about ten times). The amplification appears not to have any negative effect on the signal from the sensor since no saturation is visible on any of the signals. If saturation was present, then valuable information can be lost. Ten signals were studied and none revealed any saturation due to breathing or heartbeats. The only saturation visible was from spikes caused by sudden movements of the body when turning, kicking or moving.

### 4.1.5 Frequency analysis of PESD signal

#### Choosing a sampling frequency

Up until this point, the experimental data was sampled at 8 kHz. Some of the previous experiments, however, showed that the data recorded using the PESD consisted of frequencies much lower than 8 kHz. A more in-depth look at the frequency spectrum of the PESD data confirmed this. The FFT of some of the experimental data was taken and its frequency components studied. Figure 4.7 (a) shows the FFT of one such test. Plot (b) shows the logarithmic plot of the frequency spectrum. The logarithmic plot tends to magnify the low amplitudes which allows for closer inspection of the associated frequency content. The study showed that the relative energy of frequencies higher than about 12 Hz is almost zero and is

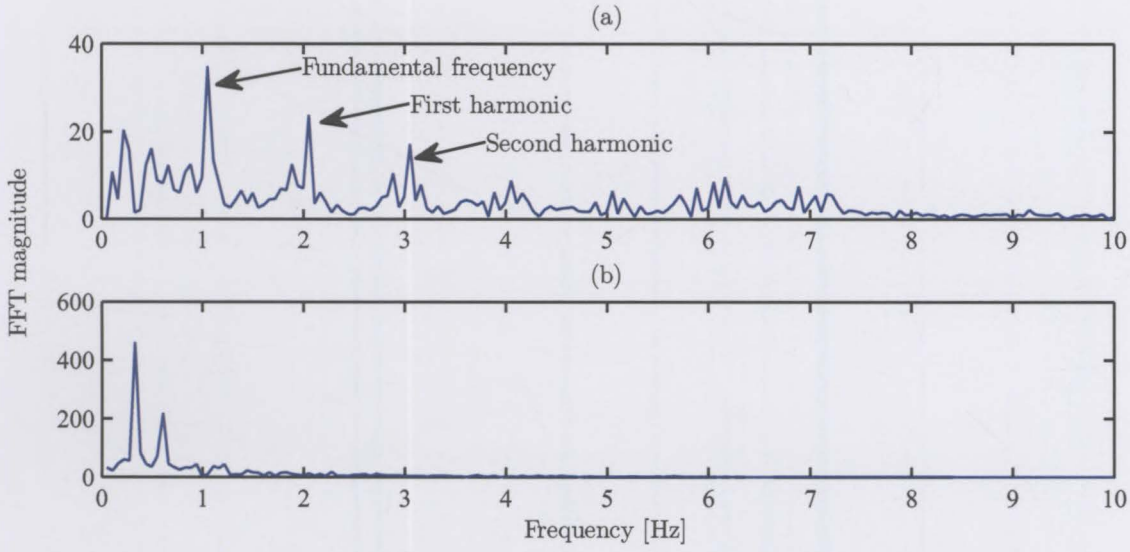


**Figure 4.8:** *Frequency plot of PESD data containing (a) only heartbeats and (b) respiration and heartbeats.*

thus of no value. According to the Nyquist sampling theorem [50], a sampling frequency of twice the frequency bandwidth (BW) of the data is required to be able to exactly reconstruct a signal from the sampled waveform using an ideal low-pass filter (Equation 4.1).

$$f_s \geq 2BW \tag{4.1}$$

A new sampling frequency of 100 Hz was chosen to be at least twice the frequency bandwidth of the data. The data used during the rest of this project was still sampled at 8 kHz (due to the hardware restriction explained in Section 3.1.2) and then downsampled to 100 Hz in Matlab.

### Identifying the frequency components present in the PESD signal

Since it has been established that there are two sources that contribute to the PESD signal (respiration and heartbeat), it seems appropriate to analyse the frequency components of each of these sources in an attempt to isolate the heartbeat frequencies.

An experiment was conducted in which the frequency spectrum (using the FFT) of the heartbeat data was compared to that of respiration plus heartbeat. The differences in the two spectra could reveal the effect of respiration and its frequency components.

Two plots are shown in Figure 4.8. The first is a plot of the FFT of a signal containing only a heartbeat, and the second is a plot of the FFT of a signal composed of heartbeats

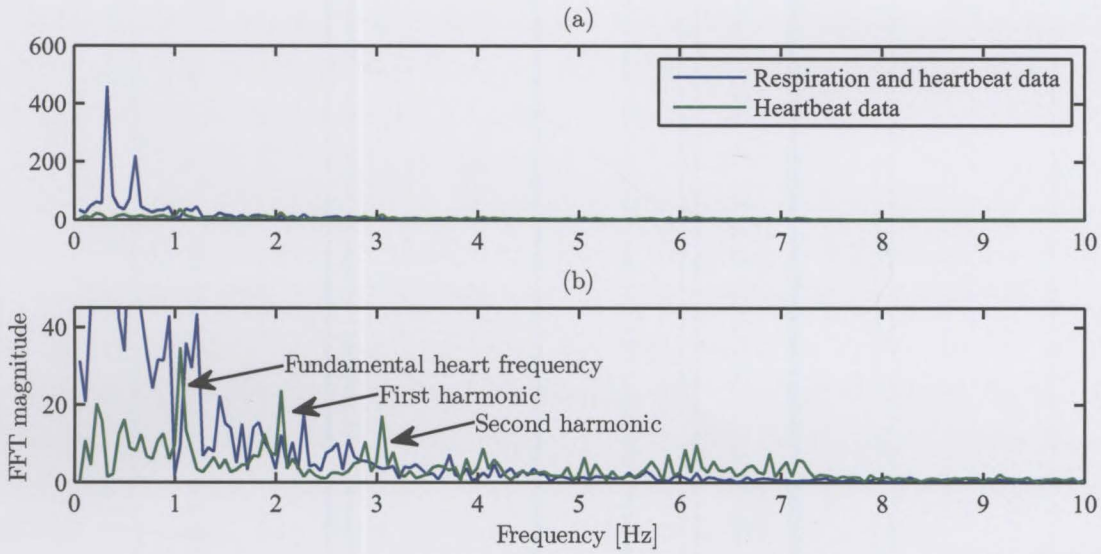


**Figure 4.9:** *Frequency plot of (a) both sets of data (respiration with heartbeats as well as only heartbeats). Plot (b) is a enlarged version of (a).*

and respiration. In plot (a), the fundamental frequency of heartbeat can be identified, as well as its harmonic frequencies. Note that the FFT magnitude of the signal containing only heartbeats is much smaller than that of the signal containing heartbeats and breathing. This confirms that the energy of the respiration frequencies is much greater than that of the heartbeat. The fundamental frequency of a heartbeat signal is a direct relation to the heartbeat tempo. For the example in Figure 4.8 (a), a fundamental frequency of $f = 1$ Hz will yield a heartbeat tempo that can be calculated as follows:

$$\begin{aligned} \tau &= 1/f \\ &= 1/1 \text{ Hz} \\ &= 1 \text{ s} \\ \textit{tempo} &= 60/\tau \\ &= 60 \text{ bpm} \end{aligned}$$

This value corresponds to that obtained from counting the ECG peaks.

In Figure 4.9 the frequency spectrum of both signals were plotted together so that their magnitudes can be seen. In plot (a), the frequency spectrum of the signal containing heartbeats is barely visible under the signal dominated by respiration. Plot (b) shows an enlarged version of the first plot. Here one can once again see the fundamental frequency of the heartbeat, and its harmonics. However, it is evident that there are much larger breathing

components present at the same frequency as the fundamental frequency of the heartbeat.

Another observation was made regarding the higher frequency components of both signals. It can be seen that the higher frequency components (above 2 Hz) of the heartbeat signal is actually larger than that of the signal containing heartbeats and respiration. At first, this seems erroneous, but can be explained by the results presented in Section 4.1.2. It was found that inhalation data contains more higher frequency components than exhalation data. The heartbeat signal used for this section's experiment was recorded as inhalation data, whereas the signal with the heartbeats and respiration obviously contains inhalation and exhalation data since the volunteer was inhaling and exhaling as normal for the recording. Both recordings were made for the same time duration. It therefore makes sense that in the signal containing both heartbeats and respiration, less of the higher frequency components will be present, and more of the lower frequencies will be present.

## 4.2 Experimental processing techniques

This section gives a description of the signal processing methods that were studied as background in the search of a method for accurately extracting the heartbeats from the PESD signal. For all the experiments below two sets of signals were used. The first set consists of signals that contain only heartbeat information while the second set of signals contain heartbeats and respiration information. Throughout this section only the data recorded from adult volunteers was used, due to reasons discussed in Section 3.3.

### 4.2.1 Passive linear filters

Filters are widely used in biomedical engineering to extract certain frequency components from signals. Measurements in clinical settings are often accompanied by unwanted noise and filters are used to remove the effect of random noise and disturbances from the signal [40].

In Section 4.1.5 it was mentioned that some of the harmonic frequencies associated with respiration coincides with the fundamental frequency components associated with the heartbeat. Also, the energy of the respiration harmonics are much larger than the energy of the fundamental heartbeat frequencies. It was therefore concluded that passive linear filters cannot separate the two sources without losing information. Linear filters were used in this project primarily to remove the majority of the lower frequency breathing noise.

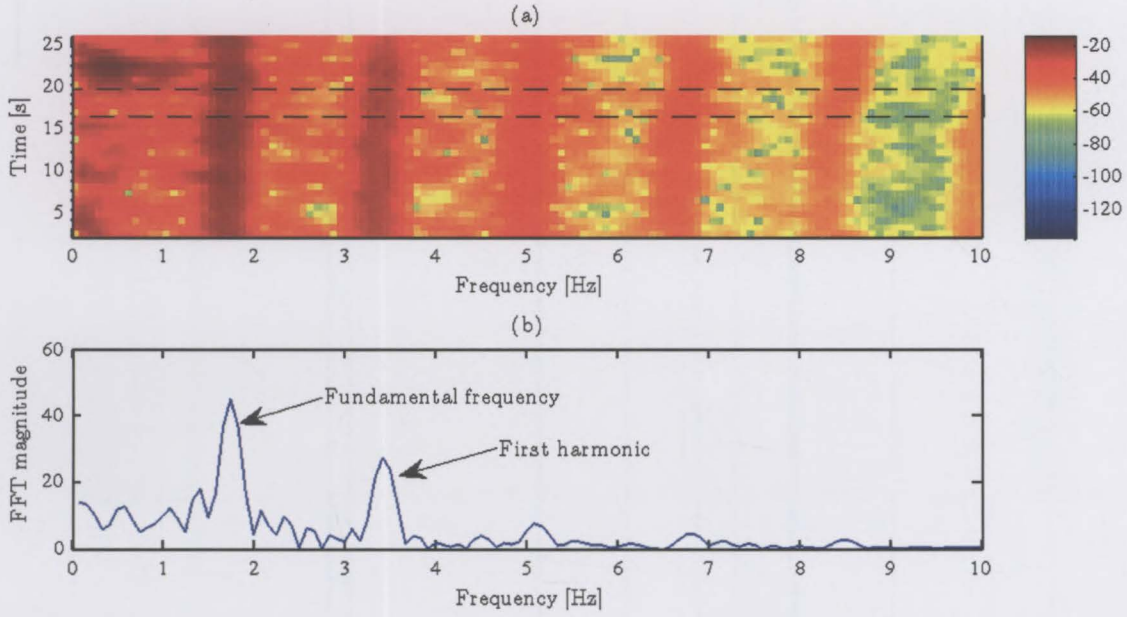


**Figure 4.10:** *Plot (a) contains the spectrogram of a signal containing only heartbeat and (b) the FFT of a section of the signal from time t=16–20 seconds. This section is indicated by the dotted line in plot (a).*

### 4.2.2 Short time Fourier transforms and spectrograms

For experimenting with the STFT, a signal was subdivided into smaller sections using a Hamming window with a width of $N$ samples. As discussed in Chapter 2, a major restriction of Fourier-based spectral analysis is its inability to provide temporal information.

The first experiment was performed using a signal containing only heartbeat information, which can be seen as an ideal signal. For this experiment, the window was chosen to have a width of $N = 1000$ samples. This value was selected for it was wide enough to include at least two heartbeats in a single window, which would then allow for the detection of periodicity. Tests were done on different window sizes, although no major improvement could be seen in the results.

The spectrogram of such a set is shown in Figure 4.10 (a). In this plot, a section extending from time $t = 16$ seconds to $t = 20$ seconds is circled with the dotted line. Plot (b) is the FFT of this section of the signal. In the FFT plot, one can clearly identify the fundamental peak as well as the first and second harmonic peaks. Note how these FFT peaks correspond to the darker areas on the spectrogram in the encircled section.

Next, the same experiment was performed with the same parameters as before, but this

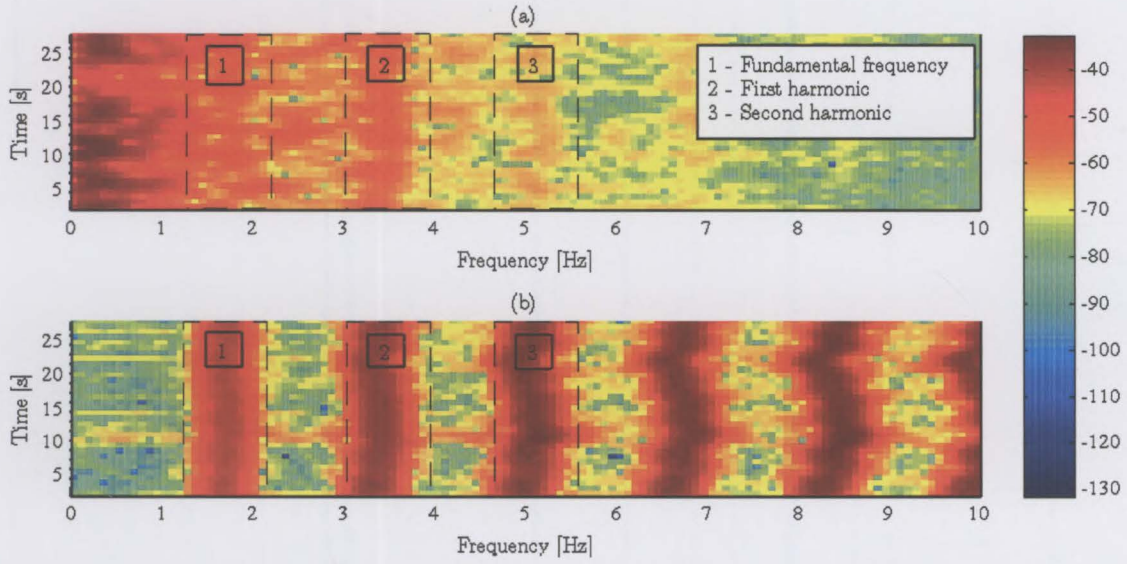


**Figure 4.11:** *Spectrogram of (a) PESD data containing only heartbeat information as well as (b) its corresponding ECG.*

time using data that contain heartbeat and respiration information. Figure 4.11 shows the plots for one such experiment. Once again, the fundamental frequency as well as the harmonics thereof are clearly visible in the spectrogram of the ECG data. By examining plot (a), however, one can see that these frequency bands (the fundamental frequency and its harmonics) are less distinct than in the previous experiment that contained only heartbeat data. The darker areas visible at the low frequencies correspond to the respiration artefacts. The fundamental frequency band is barely visible and was only recognised because of the a priori knowledge of where it should be, as seen in the spectrogram for the ECG data. Only the first harmonic can be identified without prior knowledge from the ECG spectrogram. It would be impossible, however, to know if it is indeed the first harmonic and not the fundamental frequency or the second harmonic, without knowing the location of the fundamental frequency or the second harmonic.

The plots shown for the above two experiments, were examples of good quality results chosen for the sake of explaining the process. For most of the data sets containing heartbeats and respiration, neither the fundamental frequency of the heart nor any of their harmonics were as clearly visible.

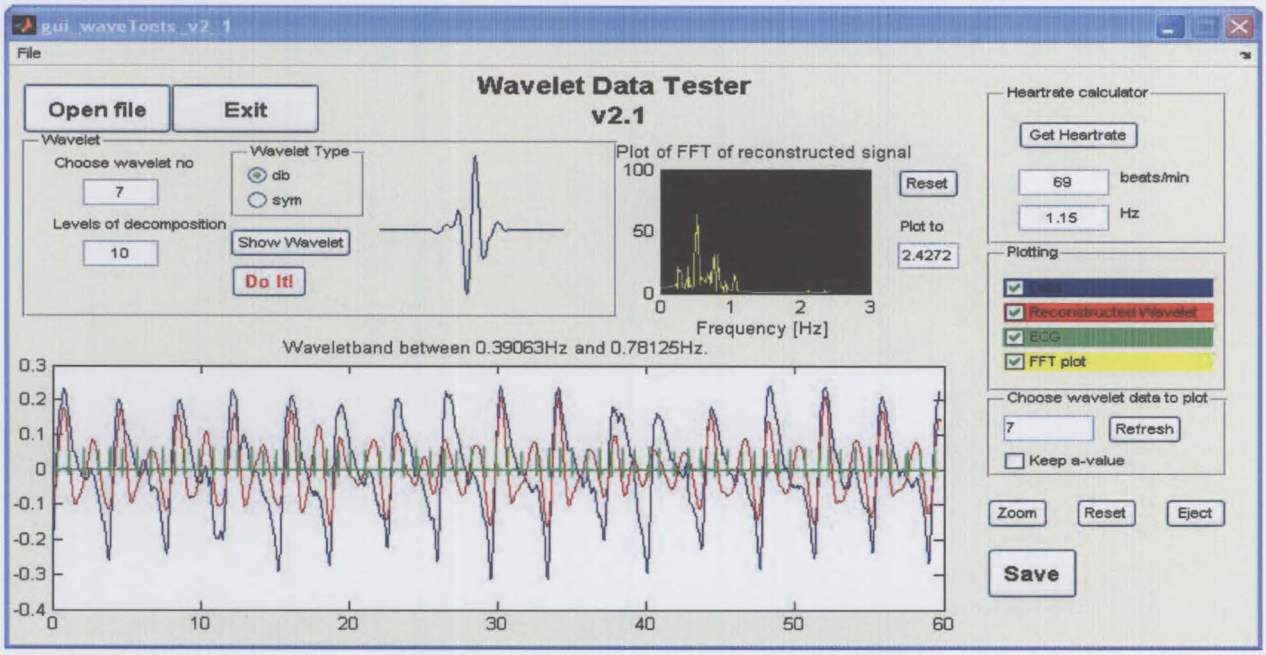


**Figure 4.12:** *A screen-capture of the GUI used for performing wavelet analysis.*

### 4.2.3 Wavelets

During the study of wavelet analysis, seven data sets were analysed and studied at different scales (See Section 2.5.3)in an attempt to find the best frequency band from which the heart rate information could be extracted. A graphical user interface (GUI) was written which allowed for easy changing of wavelet characteristics and also simplified the study of individual scales obtained from performing discrete wavelet analysis. A screen-capture of the GUI is shown in Figure 4.12.

The wavelets that were used included the Daubechies family of wavelets, as well as symlets. Initial tests were done on heartbeat data. This allowed for a wavelet to be selected that closely resembled the heartbeat of a volunteer. Figure 4.13 shows an example of an output obtained for scale 8 with a frequency band from $f = 0.49$ Hz to $f = 0.98$ Hz. Here one can see the wavelet output presenting peaks that correspond to the ECG peaks.

Figure 4.14 (b) and (c) shows two examples of how the heartbeats can be identified from two different scales. The heartbeats in plot (b) can be seen as the larger grouping of smaller peaks corresponding to the ECG peaks. In plot (c) the heartbeats can be seen with each peak from the wavelet output corresponding to an ECG peak. The example in (b) is for the frequency band from 3.91 Hz to 7.81 Hz while the example in (c) is for the frequency band from 0.98 Hz to 1.95 Hz. Plots (a) and (b) shows the same scale (scale 5)

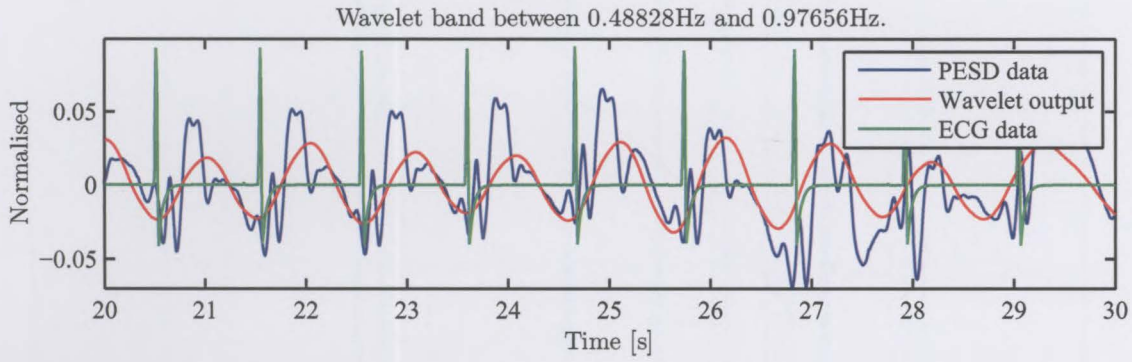


**Figure 4.13:** *Plot of wavelet output (scale 8) obtained for heartbeat data, together with the ECG and PESD recordings.*

for two different volunteers whereas plots (c) and (d) shows a different scale (scale 7) for the same two volunteers. Figure 4.14 however reveals a potential problem for reliably detecting heartbeats by using wavelet analysis. For the first scale (plots (a) and (b)), the heartbeats can only clearly be identified for the second volunteer. For the second scale (plots (c) and (d)) however, the heartbeats can only clearly be identified for the first volunteer. This shows that one can clearly obtain the heartbeats for both volunteers, but at different scales (or frequency bands). Similar observations were made for the other five sets of data.

### 4.2.4 Matched filtering

A matched filter is a filter which optimizes a desired signal by correlating one signal, $s(t)$, with another signal , $x(t)$, in order to determine the presence of $s(t)$ in $x(t)$ [44]. Suppose that a waveform, $x(t)$, was received which consists of noise $n(t)$ plus a signal, $s(t)$, of known form. One wishes to determine whether $s(t)$ is present in $x(t)$ by using a linear filter that will produce an output at time $t = \tau$ that is far greater than if $s(t)$ is absent [45]. It must however be mentioned that when the signal of known form is only a partial heartbeat for example, then the heartbeats in the received waveform can still be detected, by detecting that part of the heartbeats that correspond to the partially known heartbeat. The matched filter is a filter that works in such a way and is known to be the optimal filter for maximizing the signal to noise ration (SNR) in the presence of additive stochastic noise.

By definition, a matched filter is equivalent to performing convolution between $x(t)$ and the time-reversed version of $s(t)$. Its impulse response can be given by:

$$h(\tau) = ks(p - \tau) \tag{4.2}$$

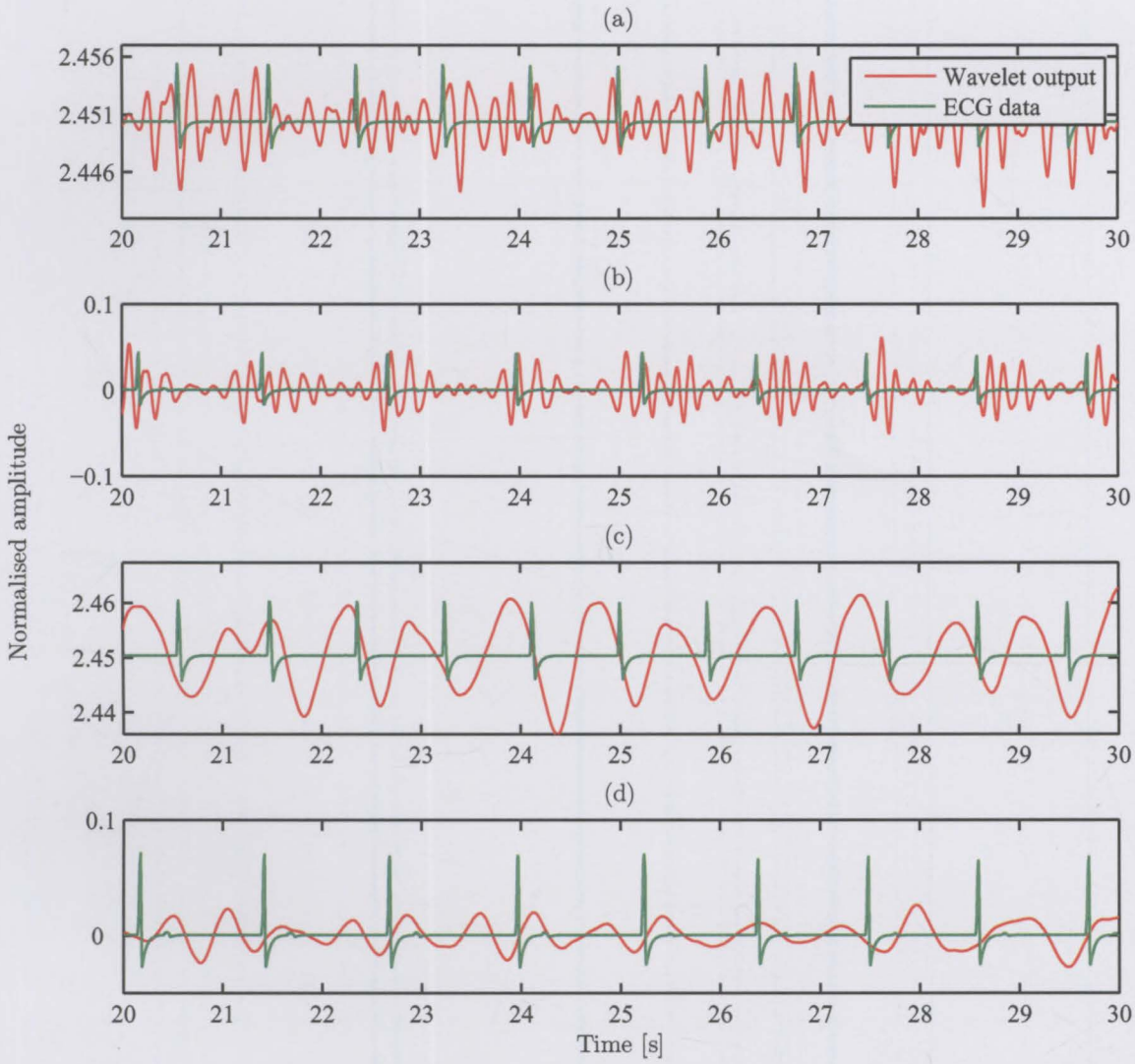


**Figure 4.14:** *Plots of wavelet outputs obtained for two volunteers. Plots (a) and (b) shows scale 5 for the two volunteers and plots (c) and (d) shows scale 7.*

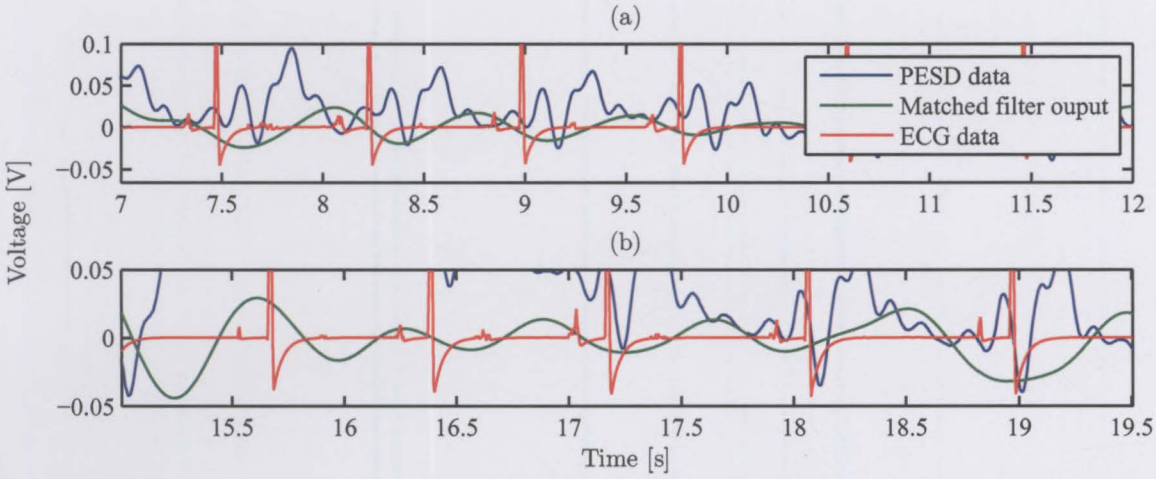


**Figure 4.15:** *Example of matched filter output for (a) signal with only heartbeats and (b) a signal containing heartbeats and respiration.*

where $k$ and $p$ are arbitrary constants [45].

An experiment was performed in which a single heartbeat was selected from a signal to serve as input to the matched filter. Matched filtering was then performed on a signal containing only heartbeats, as well as a signal containing heartbeats and respiration. Figure 4.15 shows the results for the matched filter output. From both the signals one can clearly see the peaks in the matched filter output corresponding to the ECG peaks. [17]

## 4.3 Discussion

Several methods, with their associated limitations, were discussed in this chapter. Up to this point, infant data was not available, so all experiments were done using adult data.

Wavelets and matched filtering yielded the best results for extracting heartbeats from a PESD signal. The wavelet experiments, however, revealed that different scales need to be examined in order to obtain the desired heartbeat information. Additionally, wavelet analysis is also computationally intensive. For these two reasons, wavelet analysis was abandoned and it was decided to rather design the system model using a matched filtering approach.

# Chapter 5

# System design

Regular bandpass filters are limited to filtering a set frequency range. However, a heart rate and respiration change constantly in humans and therefore a recorded signal of these events does not have a constant frequency distribution. Some sort of adaptive filter is required that will filter a signal depending on its frequency content. This led to the development of a design model that consists of a heartbeat detection part and a heart rate estimation part. The former consists of a heartbeat estimation part and the matched filtering part. The matched filter is a filter that correlates two signals and serves to detect the instant in time when the received signal appears to be best aligned with the finite-duration stored replica [51]. The purpose of the heartbeat estimation part is to adaptively estimate the shape of the waveform caused by the heartbeat, which will serve as the replica mentioned above. This chapter presents possible solutions for both the above-mentioned topics and provides discussions regarding the advantages and disadvantages of the presented approaches.

## 5.1 Heart rate estimation and monitoring

A heart rate estimation process is required to analyse a given sequence of heartbeats to determine the heart rate and its changes. The heart rate estimation process was developed before the detection process because it will serve to test the effectiveness of the heartbeat detection process. This will be the measurement tool by which the effectiveness and accuracy of the detection process will be evaluated.

The heart rate estimation process involves the estimation of the average heart rate (HR) over a certain time interval. One way in which heart rate estimation is done, is by counting the number of heartbeats in a recording, dividing it by the time duration of the recording and then multiplying it by 60 seconds to obtain the heart rate in beats per minute (bpm).

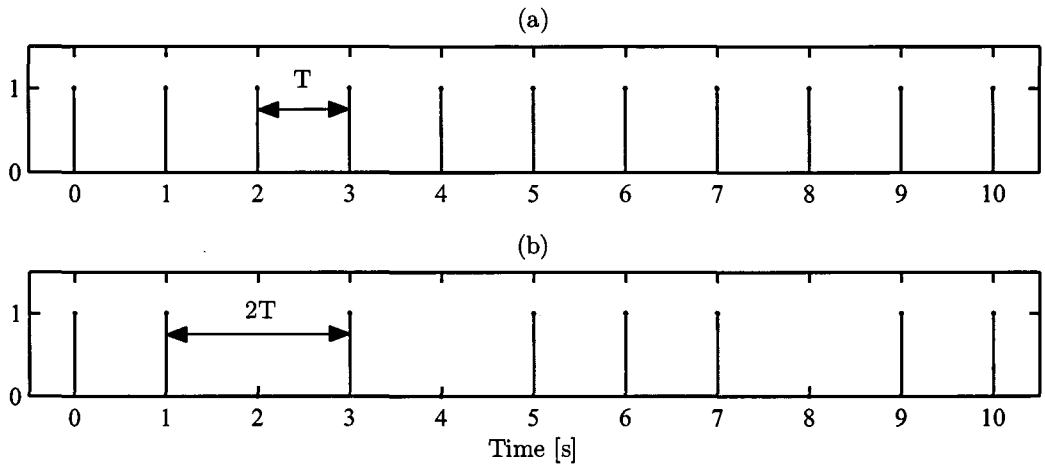


**Figure 5.1:** *Example of (a) impulses representing heartbeats spaced evenly and (b) impulses of heartbeats where some of the beats were not detected. A single spacing is labeled as T and the spacing where a heartbeat was not detected is labeled as 2T.*

Or in mathematical form:

$$\text{HR} = \frac{\text{Number of heartbeats}}{\text{duration}} \times 60 \tag{5.1}$$

This way of calculating the average heart rate however, is not very accurate if the heartbeat detection method is not very accurate. As an example, consider the impulses representing a heartbeat sequence, depicted in plot (a) of Figure 5.1. A very simplified example is used here with the heartbeats evenly spaced. From this plot it can be seen that there are eleven heartbeats in the selected time window. Counting one heartbeat peak plus the space that follows up to the next heartbeat, one will see there are actually ten heartbeat periods (from this point onwards, these periods will be referred to as "spacings"). Now, with ten heartbeats spread over a recording of ten seconds, one can use (5.1) to calculate the average heart rate:

$$\begin{aligned} \text{HR} &= 10 \text{ beats}/10 \text{ seconds} \times 60 \\ &= 60 \text{ bpm} \end{aligned}$$

If however, during the heartbeat detection process not all the heartbeats were detected, then a less accurate HR would be calculated with this formula. Plot (b) in Figure 5.1 shows the same signal, but where three of the heartbeats were not detected. Once again (5.1) can be used to calculate the average heart rate, but in this case it yields

$$\begin{aligned} HR &= 7 \text{ beats}/10 \text{ seconds} \times 60 \\ &= 42 \text{ bpm} \end{aligned}$$

This illustrates that if a heartbeat is not accurately detected, a heart rate estimation process is needed that can detect when heartbeats are skipped in order to still obtain an accurate heart rate.

By considering this example, it can be seen that one way to determine whether a heartbeat has been skipped, is to have knowledge of the time spacing ($T$) between two consecutive heartbeats. In this example the value of the spacing between two heartbeats would be two seconds in duration if a heartbeat has been skipped, whereas the normal spacings would only be one second long. It was therefore concluded that by representing the heartbeats in terms of the spacing between peaks, it is possible to obtain the correct heart rate even when some of the heartbeats were not detected. By grouping these spacings together according to their values, it would be possible to distinguish between the group of correct spacings and incorrect spacings in order to obtain a more accurate heart rate estimation.

### 5.1.1 Using a histogram to represent heart rate

The histogram is a method that groups data of equal value ranges together, by grouping them into bins that represent the ranges. The histogram displays the number of elements that are within a specified range and displays each range as a rectangular bin. The height of the bin is equal to the number of elements that fall within the range of the bin.

Figure 5.2 (a) shows a collection of impulses representing peaks obtained from a simulated heart signal. Plot (b) in Figure 5.2 is a zoomed version of plot (a) and shows examples of the spacings between consecutive peaks labelled as $T_n$, $T_{n+1}$ and $T_{n+2}$. These peaks are then clustered together according to their spacings in the histogram in plot (c). Changes in spacing size will directly be seen on the histogram. Larger spacings will add elements on the histogram that are situated further up on the time scale (such as $T_n$ and $T_{n+1}$) while smaller spacings will add elements at the lower time increments of the x-axis (such as $T_{n+2}$). It was found through iterative study on fifteen data sets, that the spacing between the consecutive peaks results in a Gaussian distribution [52]. The Gaussian function is given by

$$f_g(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-a)^2}{2\sigma^2}} \tag{5.2}$$

where $\sigma$ is the standard deviation and $a$ is the expected value of the distribution. In Figure 5.3, a Gaussian function is fitted to the distribution on a histogram plot of a recorded heartbeat signal. Heart rate changes such as tempo and variation will directly affect the shape of such a distribution and is discussed in Section 5.1.2. Detection errors such as heartbeats being skipped or extra heartbeats being detected will also change the shape of the Gaussian representation, and will be discussed in detail in Section 5.1.3

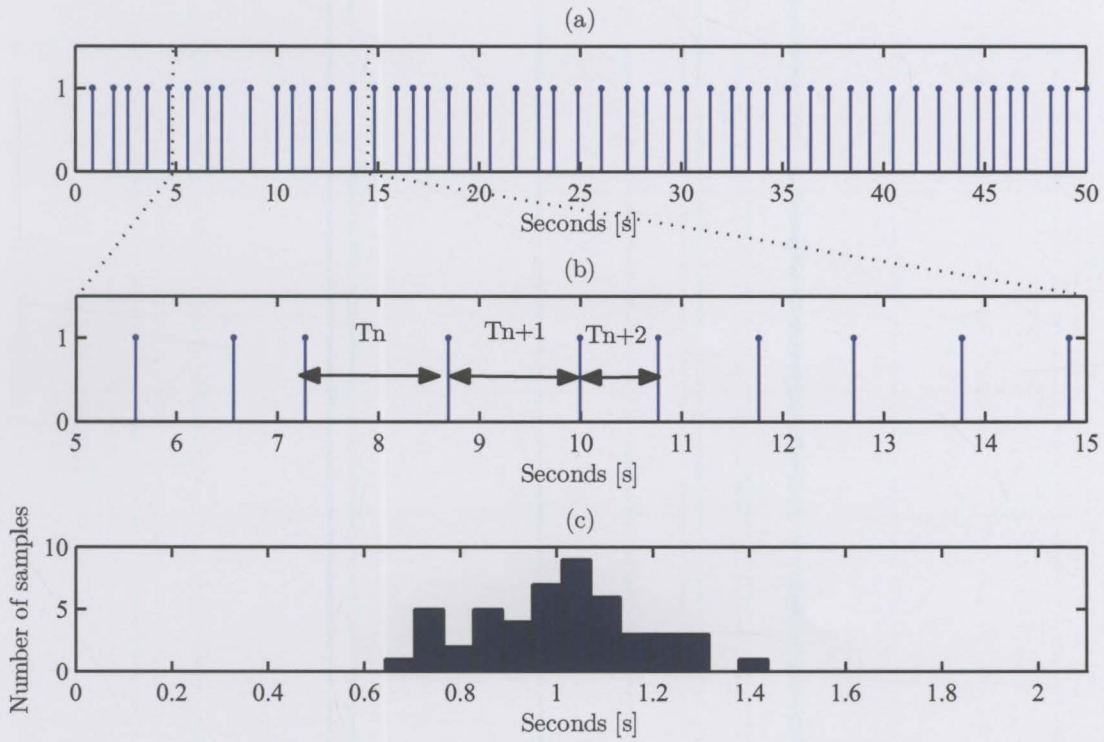


**Figure 5.2:** *Detected peaks of simulated signal is shown in (a). Spacing is shown as Tn to Tn+2 in the zoomed version in (b)which is then binned together in the histogram of the spacings shown in (c).*

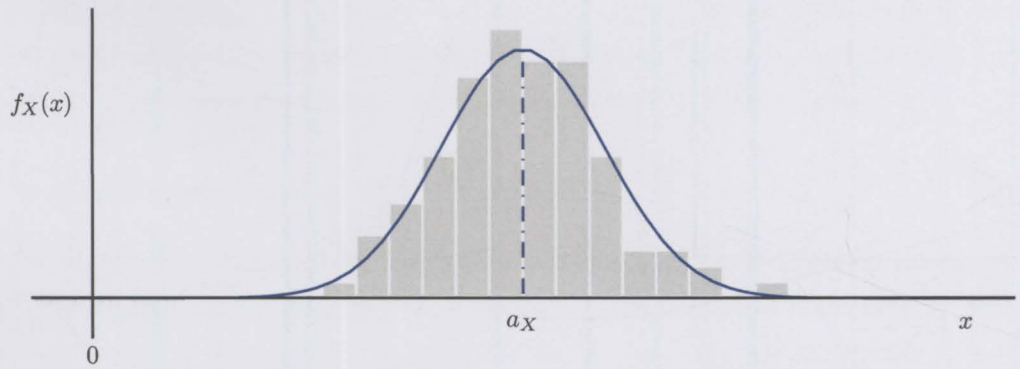


**Figure 5.3:** *Histogram and true density function for a Gaussian random variable*

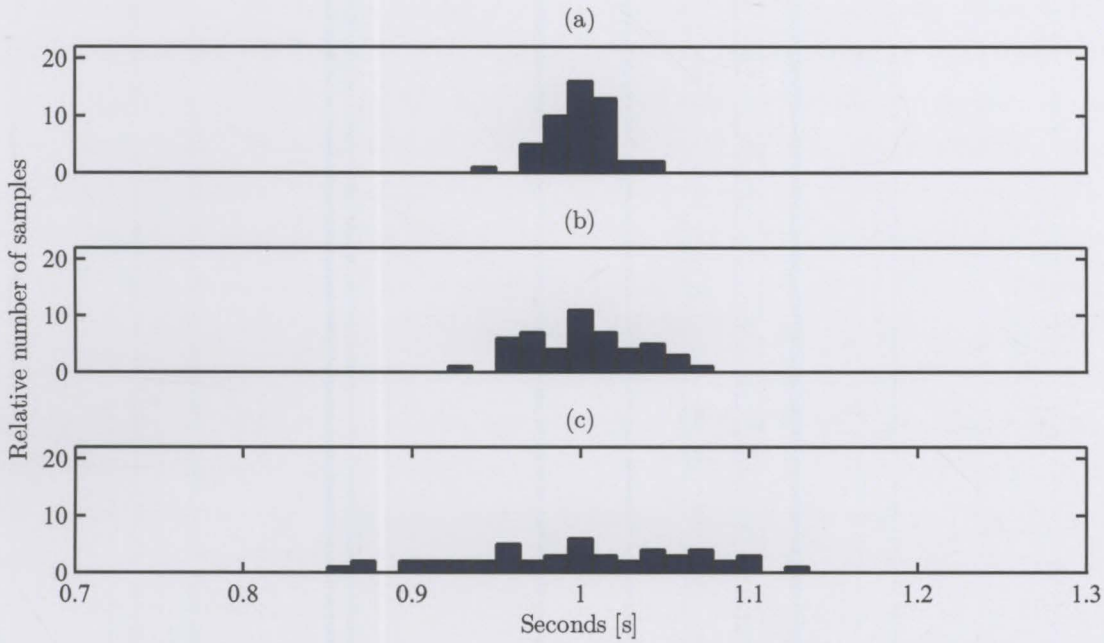


**Figure 5.4:** *Histogram plots are shown for peaks with variation in spacing of (a) 0.1 seconds, (b) 0.143 seconds and (c) 0.278 seconds.*

### 5.1.2 Interpreting the histogram as a Gaussian variable

The histogram method discussed in the previous section demonstrates a useful way to visualize the distribution of the spacings between consecutive heartbeats. As mentioned before, the peaks in the histogram plot forms a Gaussian distribution of the heartbeat spacings. The Gaussian parameters change as the heart rate changes. By studying the properties of the distribution, it is possible to extract information regarding the heart rate in a recording. Some of the parameters that determine the shape of the Gaussian distribution include the width (variation), the position (mean and median), and the height.

#### The width of the distribution

Taking the example of spacings between heartbeat peaks, if there is much variation between spacings of peaks, a greater number of histogram bins will have elements in them. This will result in a wider flatter distribution on the histogram plot. On the other hand, if the spacings are very similar in size (for example a constant heartbeat), then the elements are more focused in fewer histogram bins, resulting in the histogram plot being narrower with a higher peak.

This principle is illustrated in Figure 5.4 in ascending order of spacing magnitude variation. Three signals were generated with different spacing magnitudes of variation. For each of the three signals, a standard spacing of one second was used between peaks. A random value was then added to the peaks of each of the signals so that the heartbeats were not perfectly spaced and also so that different peak spacings could be achieved between the three signals. The random variable that was added to the first signal was between -0.1 and 0.1. The value for the second signal was between -0.15 and 0.15 and the third was between -0.28 and 0.28. The spacing between each of the peaks for the first signal thus ranged from 0.9 to 1.1. The spacing between the peaks of the second signal ranged between 0.85 and 1.15 and the spacing between peaks for the third signal ranged from 0.72 to 1.28. These values were arbitrarily chosen for illustration purposes. Plot (a) of Figure 5.4 contains the histogram of the first signal with the smallest difference in spacings among the peaks. Plot (b) contains the histogram of the second signal and plot (c) that of the third signal, which has the greatest spacing difference between consecutive peaks. It can be concluded from these plots that a greater variation in heartbeat spacings results in a flatter and wider histogram plot.

### The location of the distribution on the time-axis

The size of a spacing between two beats simply indicates time with which two beats are separated from one another. The values of the spacings are therefore a direct measure of the heart rate. Since the histogram plot shows a collection of the spacings, it effectively shows a collection of heart rates measured between two heartbeats at a time. The centre of the histogram peak is therefore an indication of the average heart rate for a given recording. As an example, two heartbeat signals were generated as a sequence of impulses. The heart rate of the first signal is 60 bpm (Figure 5.5 (a)) and therefore has a spacing of $T = 1$ s between beats. The heart rate of the second signal is 100 bpm (Figure 5.5 (b)) and therefore has a spacing of $T = 0.6$ s between beats. A sequence of random numbers between -0.1 and 0.1 were then added to both the signals so that the heartbeats were not perfectly spaced. The elements are thus not all allocated to one bin on the histogram plot, but is rather spread out in the Gaussian distribution. This was done to closer resemble the non-stationary effects of a real heartbeat.

The histogram plots for the two signals are shown in Figure 5.5 (c). The histogram of the first signal is centred at time $t = 1$ s corresponding to the average spacing value for the signal with a heart rate of 60 bpm. The histogram of the second signal is centred at time $t = 0.6$ s once again corresponding to the average spacing value for the signal with a heart rate of 100 bpm. This example shows that the position of the histogram peak on the time axis, reveals the heart rate for a given recording.

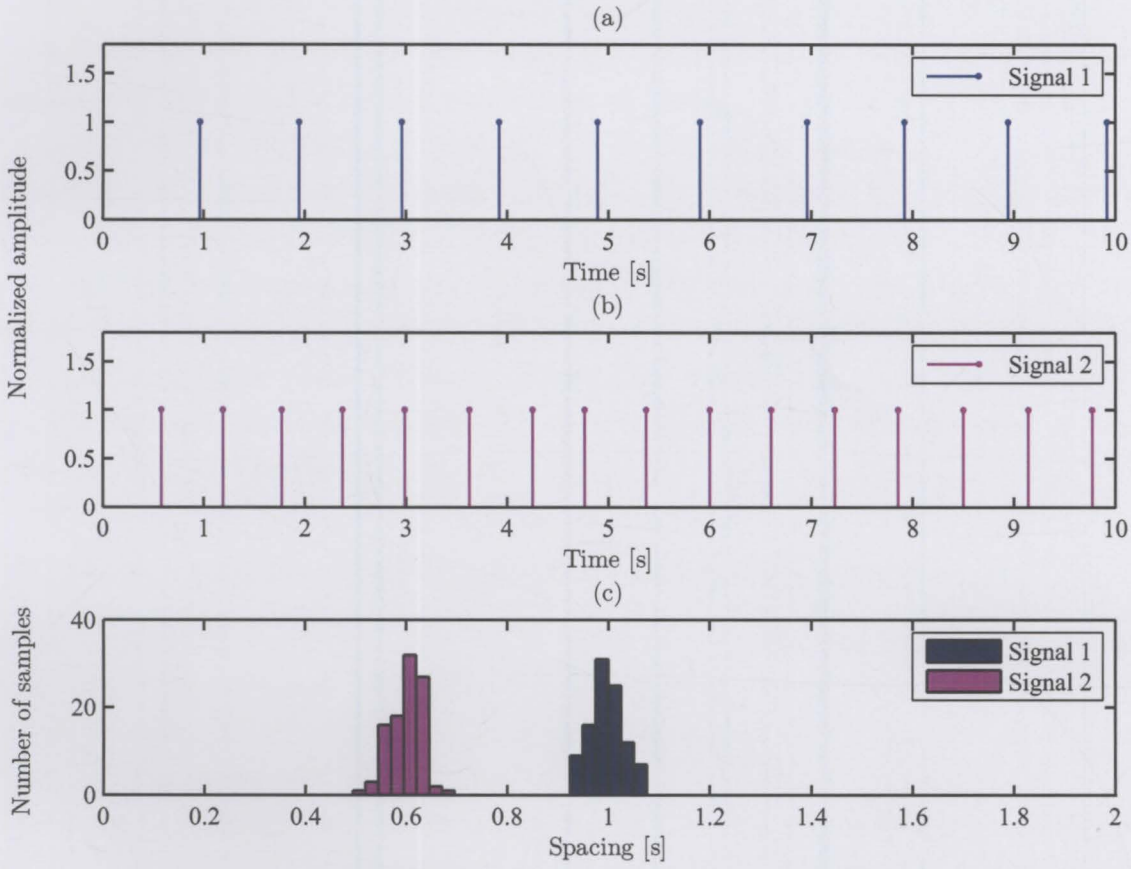


**Figure 5.5:** *Example with two simulated heartbeat signals with heart rates of (a) 60 bpm (signal 1) and (b) 100 bpm (signal 2). The histogram for the two signals with different heart rates are shown in (c).*

#### The effect of sudden change in heart rate

The next example illustrates the effect on the histogram plot of change in heart rate, typically as it would be in the case of bradycardia (sudden slowing of heart rate). An impulse version of a heart beat was generated with an initial heart rate of 140 bpm, which then suddenly drops to 80 bpm. Figure 5.6 shows a sequence of plots to illustrate how the change in heart rate can be seen on the histogram. Plot (a) shows the section of the heartbeat when the heart rate is 75 bpm with its corresponding histogram plot to the right of it (plot (e)). In plot (b) it can be seen at $t = 24$ s the heart rate suddenly slows down to 43 bpm, and the histogram plot (plot (f)) reveals a small peak at spacing $T = 1.4$ s. This peak grows to be the larger of the two peaks in plot (g) due to the larger section of the heartbeat that contains the lower heart rate of 43 bpm (plot (c)). Then, finally in plot (d), the heart rate is 43 bpm for the whole section and the histogram plot is left with only the one peak (plot (h)). The window size in this example was ten seconds. The use of a wider window results in the transition time from the one peak on the histogram to the next to be longer, but forms more defined and identifiable peaks. The use of a smaller window results in the transition to be faster, but the peaks are less distinct. There is thus a play-off between speed of detection and the clarity of the peaks.

### 5.1.3 Histogram representation of detection errors

In the previous section it was shown how a vector of heartbeat spacings can be represented using a histogram view and how changes in the spacing can be seen on the histogram. In this section, examples of change in spacing due to detection errors will be discussed and the effect on the histogram plot will be illustrated.

There are two things that can go wrong during a heartbeat detection process. The first is that heartbeats might be present, but are not detected, and the second is that interference or other distortions might cause the detection process to detect heartbeats when they are not present. The former case will be referred to as *deletions* and the latter *insertions*.

#### Deletions

During detection of heartbeats, it might happen that a certain heartbeat is just below a threshold value, and might then not be seen as a heartbeat. This peak is then referred to as a deletion since it should have been included in the array of heartbeats, but was instead "deleted" from the selection.

In the following example, the heartbeat has an average heart rate of 60 bpm, so the peaks will have a spacing of one second. A deletion will then in effect cause one of the spacings to

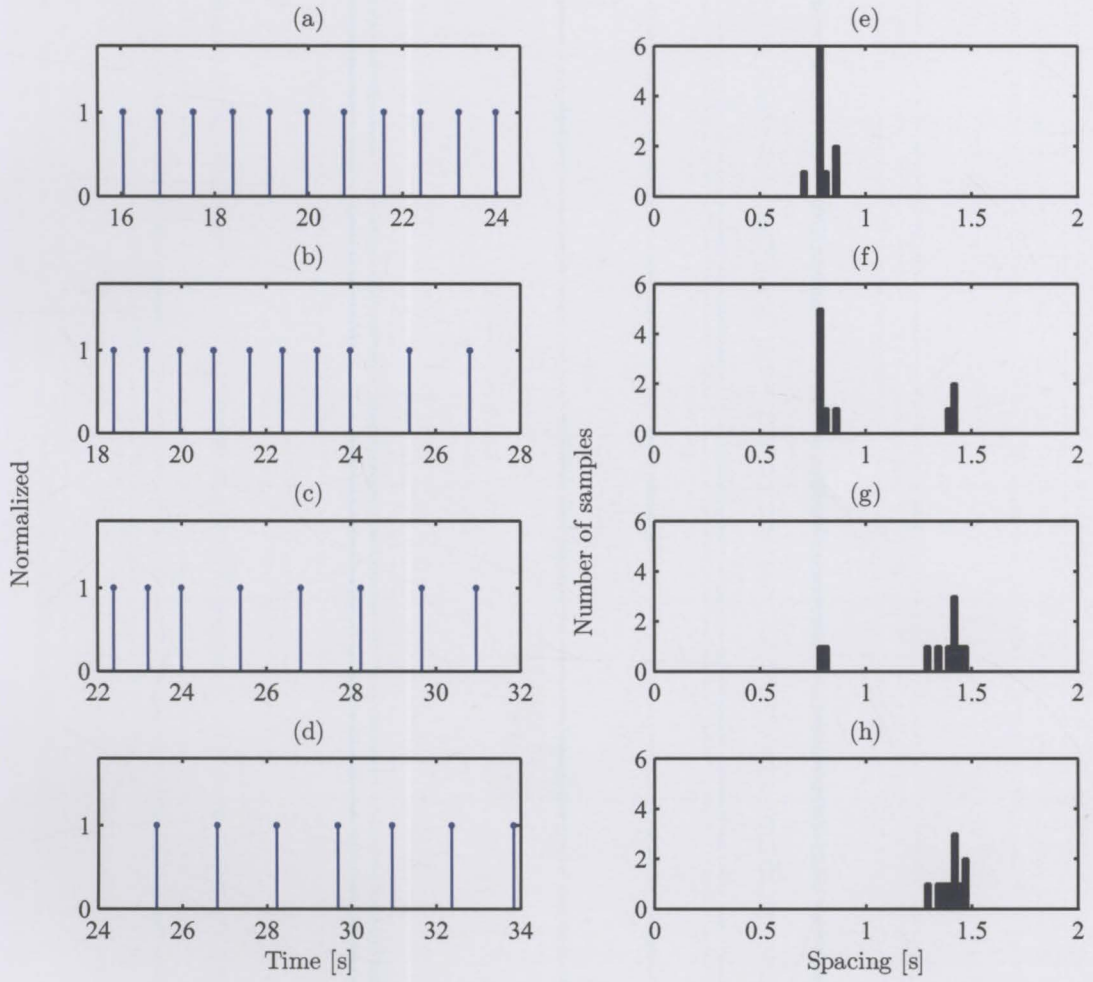


**Figure 5.6:** *Plots illustrating how change in heart rate reflects on the histogram plot. Constant HB of 75 bpm (a) forms one peak on the histogram plot at spacing=0.8 s in (e). As a sudden change is introduced in (b) at time t=24 s, a second peak appears at spacing=1.4 s (f). As time passes, a bigger part of the slower heart rate is visible (c) resulting in a larger peak on the histogram plot at spacing=1.4 s (g). Finally in (d), only the slower heart rate is present with only one peak on the histogram plot (h).*

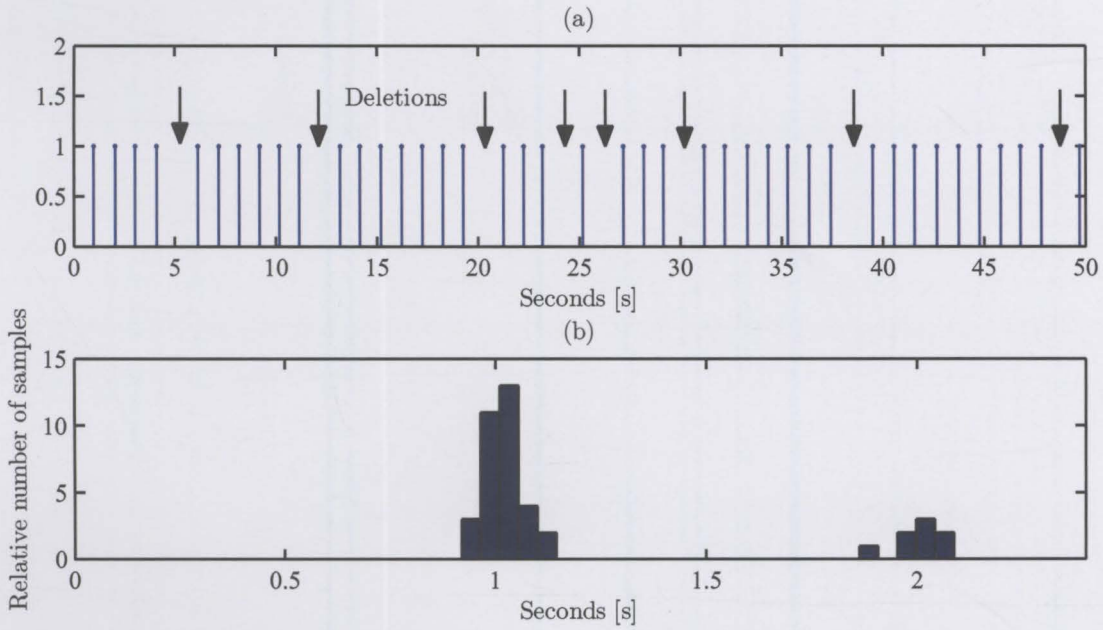


**Figure 5.7:** *Heartbeats indicated by impulses with (a) deletions indicated by arrowheads and (b) a histogram plot of the heartbeat sequence revealing the two peaks, the smaller secondary peak being the result of deletions.*

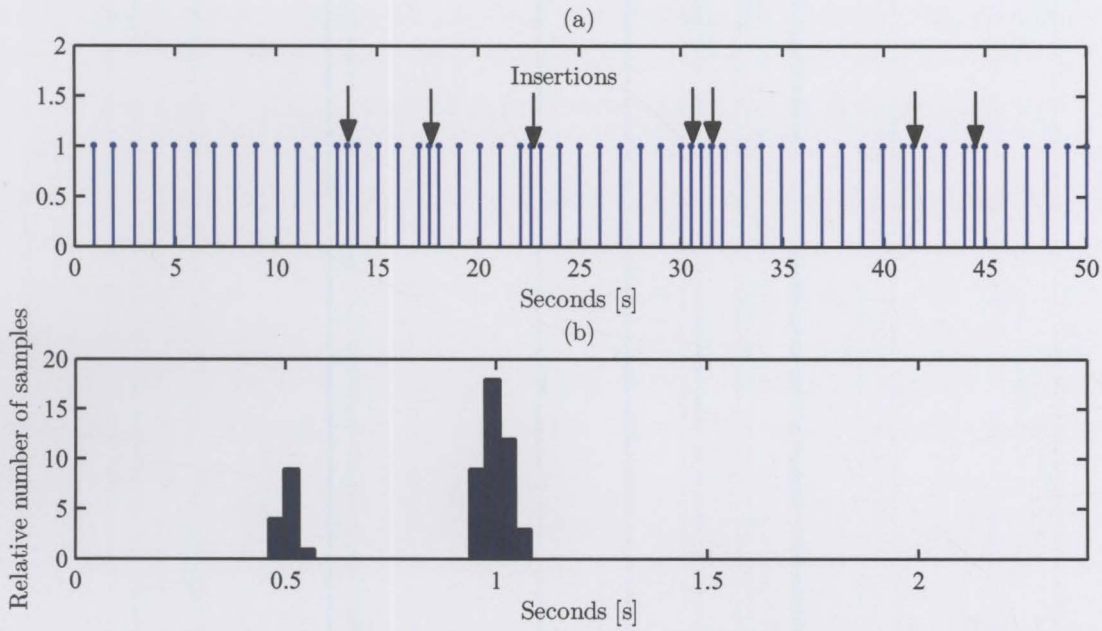


**Figure 5.8:** *Heartbeats indicated by impulses with (a) insertions indicated by arrowheads and (b) a histogram plot of the heartbeat sequence revealing the two peaks, the smaller first peak being the result of insertions.*

be equal to two seconds in length. A series of heartbeat peaks can be seen in Figure 5.7 (a) with deletions present and indicated by the arrowheads. When viewing the spacing between the peaks on a histogram plot such as in plot (b), it can be seen that deletions will result in a mixed Gaussian distribution of the peak spacings instead of just a single Gaussian distribution. There will be a major (primary) peak centred at time $t = 1$ s consisting of the normal spacing values, but also a secondary peak centred at time $t = 2$ s that consists of the spacings from the deletions.

In the case of two or more deletions existing directly after one another, the histogram plot will yield another small peak at a time $t > 2$ s. In both cases however, the main (correct) peak can still clearly be identified.

### Insertions

When there are disturbances present in a recording, it might happen that these disturbances are seen as heartbeats by the detection program. This will result in the "insertion" of extra heartbeats in between the true (correct) heart beats. These extra beats are referred to as insertions.

Figure 5.8 (a) shows a series of impulses representing the heartbeats obtained from a simulated heartbeat signal. This signal contains insertions which are indicated by the arrowheads in the figure. These insertions were inserted in the middle between two existing heartbeat peaks. Taking the example in the above section with an average spacing between beats being $T = 1$ s, the insertions will cause spacing of about $T = 0.5$ s between heartbeats. On the histogram plot in Figure 5.8 (b) it can be seen that a minor peak centred at time $t = 0.5$ s is present due to the presence of insertions in the heart signal with the major peak still centred at time $t = 1$ s.

In the case of two or more insertions existing directly after one another, the histogram plot will yield another small peak at a time $t < 0.5$ s. The main (correct) heartbeat peak will still be visible.

### Presence of both insertions and deletions

When both insertions and deletions are present in a recorded signal, the effect of both the insertions as well as the deletions on the histogram can be combined. Figure 5.9 illustrates such an example with insertions and deletions being present in the recording. This simply results in both insertion peaks and deletion peaks being present together with the main (correct) peak.

### Limitations of the approach of spacings

The effect of insertions and deletions is not only limited to contributing to the size of a secondary peak consisting of other insertions or deletions. When an insertion is present between two correct heartbeat peaks, then the insertion in effect causes two spacings to exist that contribute to the insertion peak. This is because the spacing that would have been there (if the insertion was not present) is divided in two by the insertion, creating two new spacings of half the size. The one spacing is on the left of the insertion and the other on the right. This has a twofold disadvantage: The first is that when an insertion is present, there are one less correct spacing to contribute to the main peak on the histogram. The second is that for every one insertion, two insertion spacings are created. This means that if half of the correct heartbeats has insertions between them, the insertion peak will have double the number of elements compared to the main peak. Once such example is shown in Figure 5.10 (b). Plot (a) contains the original heartbeat signal with six spacings between the peaks. In Plot (b) it can be seen that three insertions were added. By counting the spacings between peaks, it can be seen that the introduction of three insertions resulted in six insertion spacings ($T = \frac{1}{2}$ s) being present and the normal spacings ($T = 1$ s) being reduced to only three spacings.

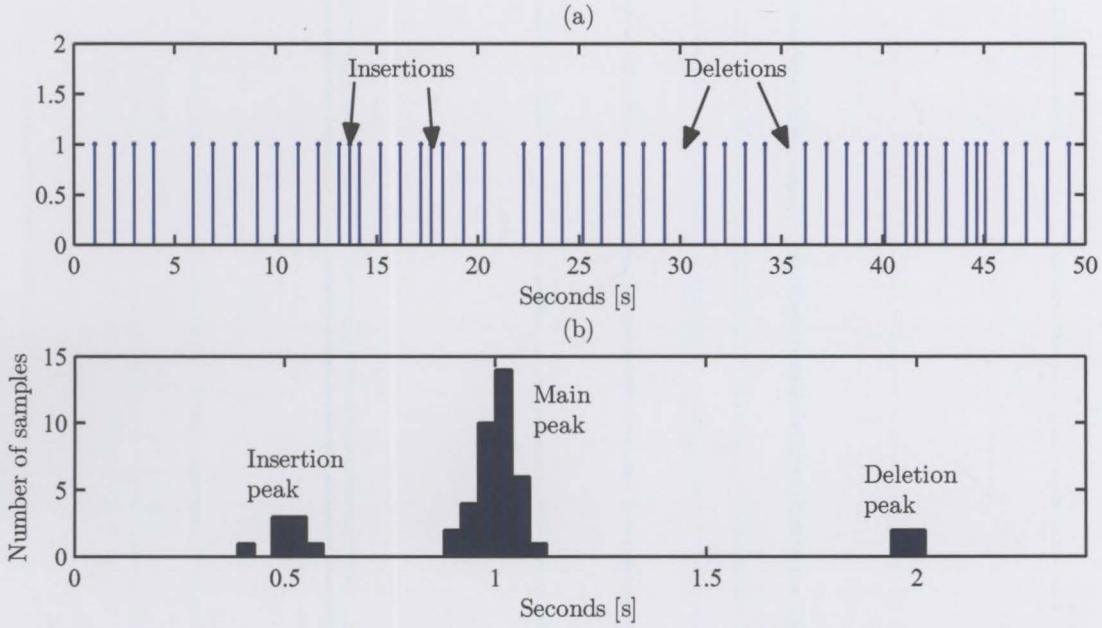


**Figure 5.9:** *Impulse representation of a sequence of heartbeats with (a) insertions and deletions being present is shown with (b) its effect on the histogram plot.*

The effect of deletions is similar to that of insertions, but in a different order. The presence of a deletion causes two normal spacings to be removed, which is then replaced by only one deletion spacing. For the example in Figure 5.10 (c) there were once again six normal spacings ($T = 1$ s) before the two deletions were added. The addition of the two deletions reduced the normal spacings by four and added two deletion spacings ($T = 2$ s).

In summary, the presence of insertions creates an insertion peak on a histogram plot that grows at double the rate of insertion addition and causes the main peak to shrink at the same rate as insertions are added. On the other hand, the presence of deletions creates a deletion peak that grows at the same rate of deletion addition and causes the main peak to shrink at double the rate as deletions are added.

### 5.1.4 Statistical representation of histogram peak

Up to this point it has been shown how the position and shape of the spacing distribution peak on the histogram plot reveal the heart rate information of a recording. The histogram plots however served as a visual aid in understanding the distribution of heartbeat spacings. In this section, mathematical methods of reading the heart rate information from the distribution peaks will be discussed.

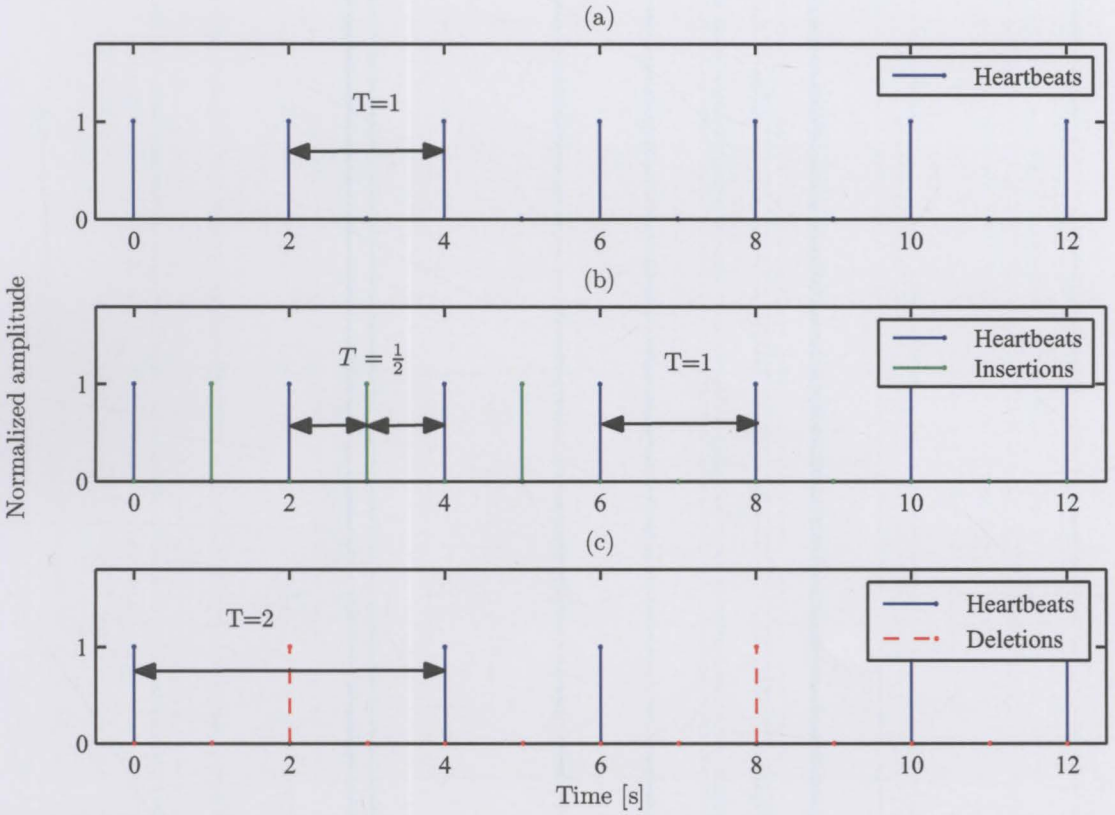


**Figure 5.10:** *Impulse representation of (a) a sequence of heartbeats with the spacings T=1. Plot (b) contains the same sequence of heartbeats with insertions. The insertion spacings are* $T = \frac{1}{2}$. *Plot (c) contains the same sequence of heartbeats, but with two deletions present. The deletions spacings are T=2.*

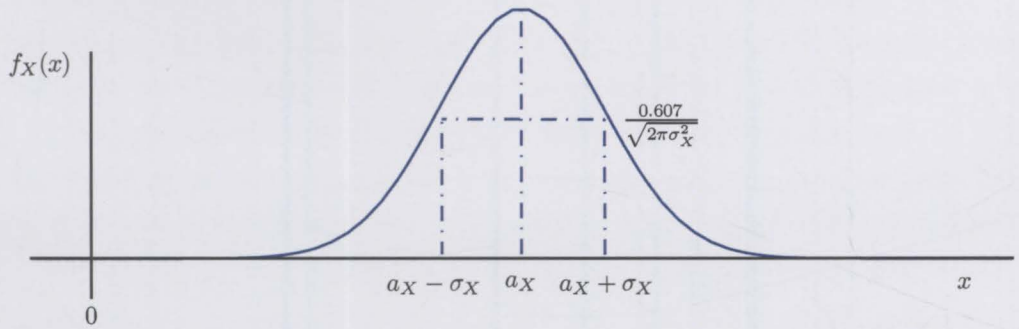


**Figure 5.11:** *Gaussian distribution showing the mean* $a_X$ *and the standard deviation* $\sigma_X$.

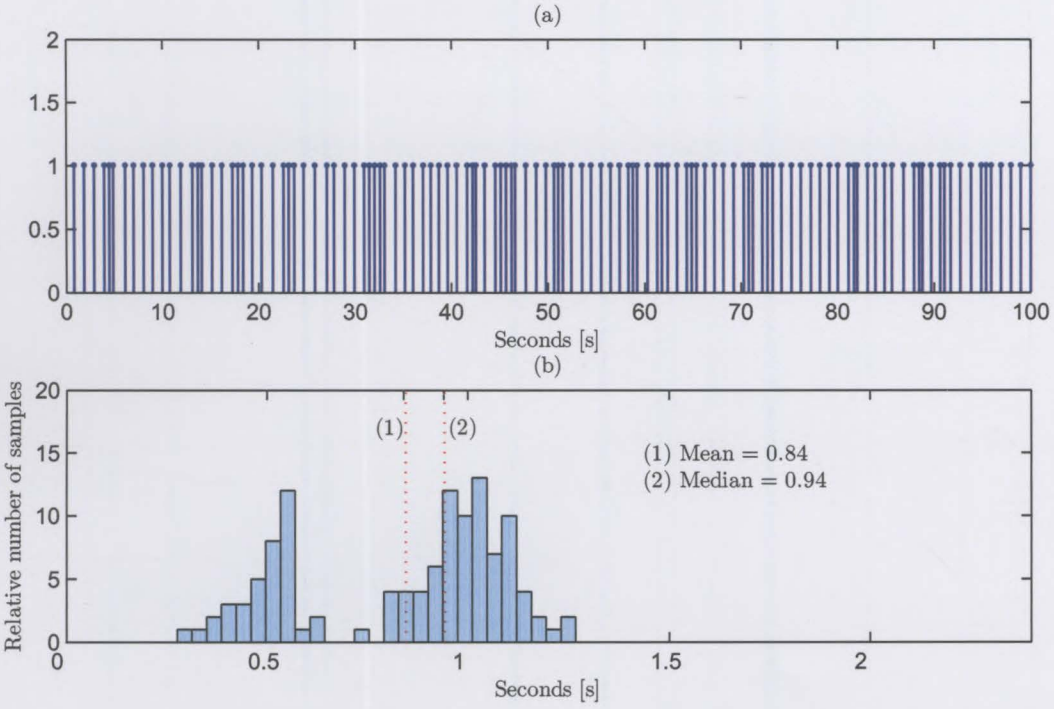


**Figure 5.12:** *Plot containing heartbeats with insertions (a) with histogram (b) showing mean and median values*

### Mean and median

The mean or expected value of a random variable is its average and will be denoted as $\overline{X}$. Calculating the mean of the spacings between consecutive peaks will yield an average spacing which directly relates to the average heart rate. The mean of the distribution can then be compared to set limits, to determine if the heart rate is within safe limits. If the mean of a distribution is too great then the heart rate is too slow (Bradycardia) and if the mean of a distribution is too small, then the heart rate is too fast. On the histogram plot of the spacings with only one Gaussian distribution, the mean $\overline{X}$ will be a value that is equal (or very close) to the spacing value in the middle of the Gaussian distribution.

While the mean gives the average value of a set of data, the median gives the middle value of the set. Peebles defines the median as that value for which the probability is 0.5 for which half the values of random variable $X$ will not exceed the median [52, p .60]. With a set of data consisting of $N$ values, the median would be the $\frac{N}{2}$-th value in the set. For this reason, the median is more immune to values that are far beyond the rest of the data set.

As an example, a heartbeat signal was generated which included insertions. This can be seen in Figure 5.12 (a). The histogram of the heartbeats (Figure 5.12 (b)) reveal the

presence of the two peaks (correct peak and insertion peak). The presence of the smaller insertion elements causes the mean value to lie more towards the middle of the two peaks. The median of the series of heartbeat spacings is however still much closer to the centre of the correct peak and thus yields a more accurate estimation of the heart rate.

Both the mean and the median gives an indication of the average heart rate of a recording, but from the above examples it is concluded that the median gives a more accurate estimation of the heart rate in the presence of data elements that are out of bounds.

#### Variance

The second central moment about the mean of a random variable $X$ is called the variance, and uses the notation $\sigma_X^2$ [52, p .82]. Variance is given by

$$\sigma_X^2 = E[(X - \overline{X})^2] = \int_{-\infty}^{\infty} (x - \overline{X})^2 f_X(x) dx \tag{5.3}$$

The standard deviation of $X$ is the positive root $\sigma_X$ of the variance. The standard deviation is a measure of the spread of a function about its mean [52, p .82]. It thus gives the width of the distribution peak which is an indication of the variation in heartbeat spacings.

### 5.1.5 Accuracy of measured heartbeats using statistics

The first few experiments showed how the histogram representation of the spacings between peaks reveals certain heartbeat information. All of the above-mentioned experiments were done on simulated heartbeat signals. This section however, illustrates how data recorded from volunteers will be evaluated using the histogram representation.

The reason for the recording of the ECG data is to evaluate the PESD data. It therefore makes sense that the processing to be done on the PESD data should also be done on the ECG data so that the accuracy and efficacy of the methods can be examined. The ECG data supplies ideal reference for determining the heart rate since it measures the electrical activity of the heart.

#### Converting ECG data to an impulse version of heartbeats

A program was written using Matlab to create an impulse version of the heartbeat of a given ECG recording. The program uses the gradient between two consecutive points to detect the upward and downward slopes of the QRS peaks in an ECG recording. The gradient threshold for deciding the validity of a peak was determined by setting the required threshold for the slope of a peak as high as possible while still allowing all the heartbeats to be detected, and

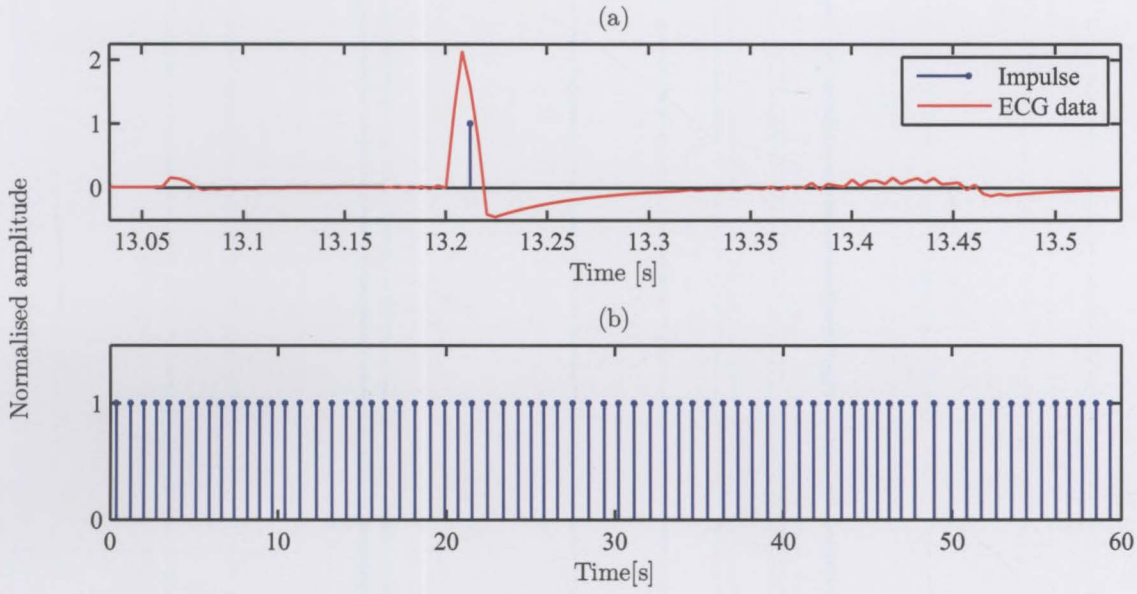


**Figure 5.13:** *Plot containing (a) a single heartbeat from an ECG signal with the corresponding impulse representing the heartbeat. This impulse forms an array of impulses representing the heartbeats as seen in (b).*

then setting it as small as possible without resulting in the detection of secondary peaks. The mid point between these two gradient values was then used as gradient threshold for heartbeat peak validation. If a peak had a slope with a gradient greater than the threshold, it was declared to be a heartbeat peak. Next,an impulse value was created (Figure 5.13 (a)) in another array which corresponds to the positions where these heartbeat peaks were detected in order to generate an array consisting only of impulses corresponding to the time instances of the heartbeats (Figure 5.13 (b)). This method for detecting the heartbeats in an ECG signal proved to be 100 % accurate. Fourteen sets of data were used in the experiment to determine the accuracy of creating an impulse version of heartbeats from an ECG signal. The impulse representation was created with the program, and then compared to the original ECG data. If a heartbeat peak on the ECG data had a corresponding impulse, then the impulse is deemed correct. If the impulse however, was not present at the ECG peak or was not at the correct location, then it was declared to be a false impulse. Table 5.1 shows the results achieved for three of the data sets that were used in this experiment.

**Table 5.1:** *Accuracy of converting ECG signal to sequence of heartbeat impulses*

| Data | Correct impulses | False impulses |
|---|---|---|
| volunteer 1 | 74 | 0 |
| volunteer 2 | 83 | 0 |
| volunteer 3 | 75 | 0 |
| **Total accuracy :** | | 100% |

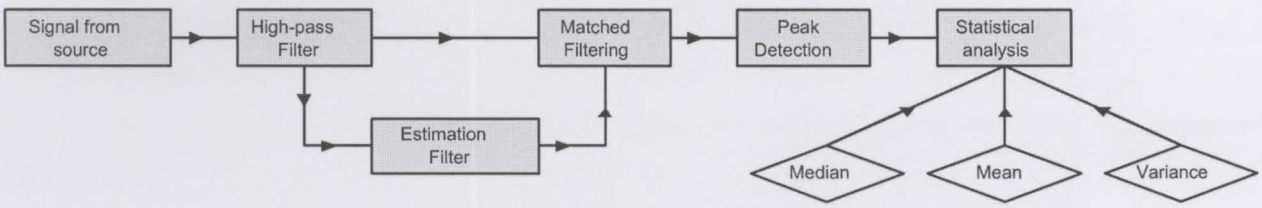


**Figure 5.14:** *Block diagram of the complete proposed system design model*

## 5.2 System design model for heartbeat detection

A complete system design model is proposed in block diagram form in Figure 5.14 which includes the heartbeat estimation, matched filtering for heartbeat detection as well as the peak detection process discussed in the previous section. Data recording and heartbeat detection were discussed earlier in this report and will only be mentioned briefly in this section.

### Estimation filter

Because only filtering out the respiration artefacts from a signal does not yield a reliable signal consisting of only the heartbeats, the estimation filter compares the frequency components of numerous signals (that has been high-pass filtered) over time and constructs an estimate of the shape of the heartbeat waveform. This filter gets a length of data from the source and as a means of adaptive filtering, it combines its existing filter coefficients with new coefficients created with the new length of data. The filter is thus being trained through numerous filtering of signals to estimate a more accurate filter for recognizing the heartbeat waveforms. Filter coefficients are then fed into the matched filter. The estimation filter is discussed in more detail in Section 5.4.

### Matched filter

The matched filter uses the filter coefficients created by the adaptive filter, and filters the incoming signal from the source. The matched filtering procedure produces numerous peaks of which the greatest corresponds to the heartbeats present in the original signal. The matched filter is discussed in more detail in Section 5.3.

### Peak detection and detecting periodicity

The peak detection phase finds all the greatest peaks within determined thresholds and creates a vector list of them. The search for periodicity is performed on the signal received from the peak detection step. The most substantial periodic sequence will yield the sequence of consecutive heartbeats.

### Statistics

The periodic signal yields a Gaussian distribution on which statistical analysis is then performed to determine whether the periodicity detected is within limits for being a reliable heartbeat.

## 5.3 Matched filtering

As discussed in Section 4.2, the matched filter requires a known signal form as input. The matched filter receives this signal from the estimation filter (to be discussed in Section 5.4) which is a close approximation of the average heartbeat waveform. The received data is then time-reversed so that the first sample is at the end and the last sample is now first. A software filter is then implemented using the MATLAB command *filter*. This filter is a direct form II transposed of the standard difference equation:

$$\begin{aligned} a(1) * y(n) = b(1) * x(n) + b(2) * x(n-1) + ... + b(nb+1) * x(n-nb) \\ -a(2) * y(n-1) - ... - a(na+1) * y(n-na) \end{aligned} \tag{5.4}$$

### 5.3.1 Setting up a matched filter for tests

One of the first questions that arose when using the matched filter was deciding what size (window length) the data set should be that will be processed. An experiment was conducted using limits as indicated by literature which defines when bradycardia becomes dangerous (refer to the Section 2.1.1). The conventional threshold for an alarm to be triggered on an apnea monitor is when the heart rate drops below 80 bpm for more than 15 seconds [21].

The desired window length should therefore allow for the system to be able to detect a heart rate of lower than 80 bpm within less than 15 seconds. For the purpose of this study, it was decided to use a window size which will allow for bradycardia to be detected. As a result, the longest window length that will allow a sudden drop in heart rate to be detected within 15 seconds should be used.

In order to determine the exact window size that conforms to the above criteria, a simulated impulse version of a sequence of heartbeats was created in Matlab. A simulated heartbeat sequence is used because of the difficulty of obtaining a recorded bradycardia event.

The simulated heartbeat has a heart rate of 120 bpm which suddenly drops to 60 bpm. These values were arbitrarily chosen above and below the conventional threshold consecutively. The exact values of the heart rates were initially thought not to be of much importance since the experiment was aimed only to detect the sudden change in heart rate within 15 seconds. However, it was shown previously that a higher heart rate will have more heartbeats within a window and will therefore result in a higher histogram peak. Also, a very slow heart rate will have few peaks within the window period and will result in a small histogram peak. If the heart rate therefore changes from very high to very low it will take longer for the second peak to grow beyond the size of the initial peak. As an extreme example, when the heart totally stops, no more heartbeat peaks will be seen so a secondary peak will not be formed at all. The first (initial) peak will however still be visible and will shrink as time progresses. The first peak will therefore only be 'smaller or equal' to the secondary peak once all the faster heartbeat peaks are outside the window. Therefore it was decided to include this extreme case into deciding the length of the window. Irrespective of the initial heart rate or the value of the sudden drop in heart rate, the window must be able to accommodate it. In the worst case (heart ceases to beat) therefore, the change in heart rate will be seen after a maximum time $t$ = (length of window). It was therefore decided to use a window length of fifteen seconds.

The criteria chosen to decide when the heart rate has changed to the new, lower value is when there are more elements in the secondary histogram peak than in the first. Keep in mind that as more of the slower beats are included in a window, more of the faster beats are excluded, resulting in the first peak shrinking while the second peak grows. The time taken when the first heartbeat of slower heart rate is detected to the time when the secondary peak contains more elements than the first, is defined as the time it takes to detect bradycardia (according to the criteria explained above).

The sequence of heartbeats in Figure 5.15 (a) has a heart rate of 120 bpm with its corresponding histogram in plot (d). In plot (b) one can see the slower heart rate of 60 bpm is introduced at time $t = 20$ s. Its corresponding histogram in plot (e) reveals the introduction

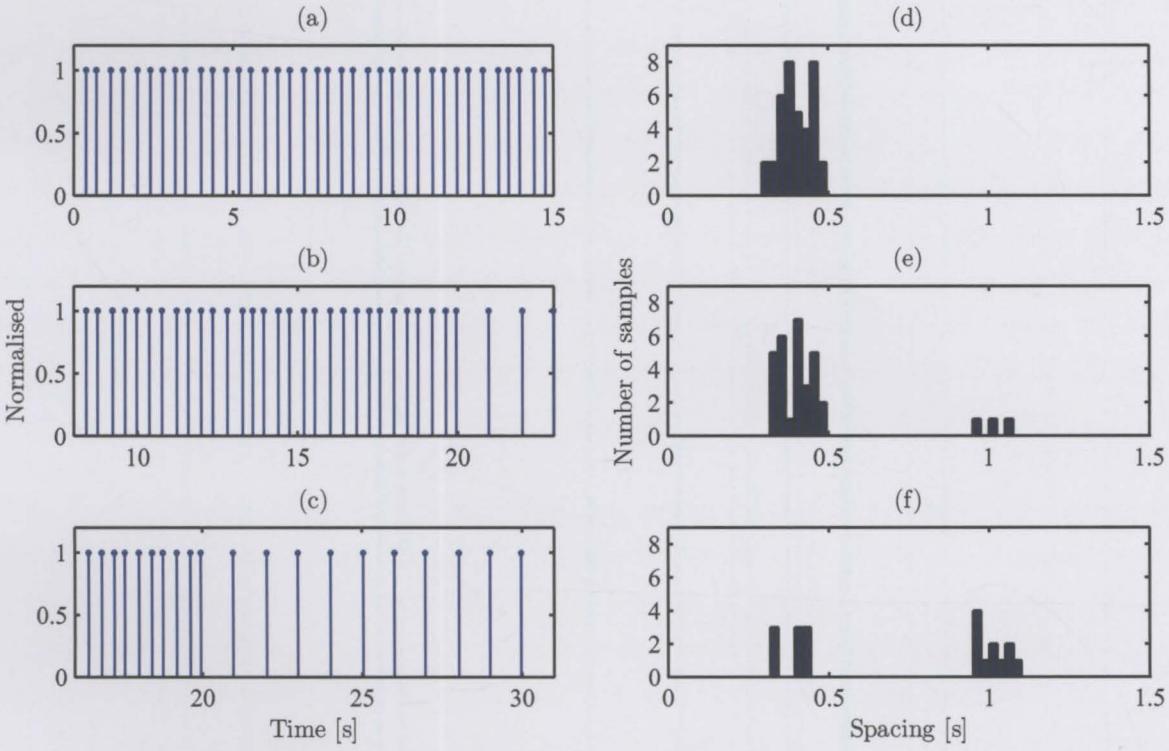


**Figure 5.15:** *Illustration of how a sudden drop in heart rate can be seen using the histogram plot.*

of the slower heart rate by the presence of the smaller peak centred at spacing $T = 1$ s. Plot (c) shows the window of the signal when the second histogram peak has grown larger than the first. From this plot it can be seen that the time taken from the presence of the first slower beat to when the second histogram peak grew larger than the first, is eleven seconds.

## 5.4 Estimation of the heart signal

The purpose of the estimation filter is to estimate the shape of the heartbeat waveform as accurately as possible. This will then be used as the *a priori* known input signal to the matched filter in an attempt to detect the presence of heartbeats.

Because the heart rate of a person is constantly changing over time, using a sequence of heartbeats as filter coefficients to the matched filter will not suffice. Even if the *a priori* known heartbeat sequence is a perfectly clean signal (without white noise or lower frequency breathing artefacts) and the input to the matched filter is also without any noise, the change in heart rate results in the possibility that there might be no overlap between the source and the filter during matched filtering. For this problem it is probably better to use a single heartbeat to determine the filter coefficients to the matched filter, and treat the heartbeats at the input of the filter as echoes of the single heartbeat with different delays.

But obtaining a single heartbeat that could be used for any input is impossible since there is so much variation in the shape of the waveform between different persons and it even differs significantly over time for a single person. It is therefore also essential to adapt the system filter to the current waveform of a heartbeat in order for it to continuously track the heartbeats' location in time. Biomedical signals are often signals with unknown or only partially known physiological components that may be periodically received [53]. Due to these factors the adaptive estimation filter must allow change in the shape of the heartbeat waveform and still be able to recognize a heartbeat.

To obtain a single instance of a heartbeat, knowledge of the composition of the PESD signal is required. Obtaining a single heartbeat is possible if one looks at a given signal and identifies a heartbeat, and then isolating it by removing the data before and after the signal. This approach is however limited to human interaction and the assumption is that the observer will select the correct section as a heartbeat. This approach is not possible here since it requires the use of a computer, and the PESD was designed to work without any prior set-up or configuration. An automated method of selecting a heartbeat is therefore required.

### 5.4.1 Model of PESD data

In Section 4.1 the composition and origin of the PESD data was discussed. Next however, a mathematical method of constructing a typical PESD signal will be explained. As a simplified design, one might model the respiration as a periodic function of frequency smaller than $f = 1$ Hz. The higher frequency harmonics caused by respiration will be ignored to simplify the model, so a sine wave of frequency $f = 0.6$ Hz is used to model the respiration artefacts in the PESD data. The cardiovascular part of the signal can be modelled as an impulse train, representing the time instances of the heartbeats, convolved by a single heartbeat. This results in a sequence of similar heartbeats. By adding the respiration and cardiovascular parts together, one obtains a simplified version of a typical PESD output signal. This process is illustrated in Figure 5.16.

It is therefore theoretically possible to reverse this process. When observing the frequency plots, one can filter the majority of the respiration peaks in plot (j) out to remain with the spectrum in plot (h). Noting that plot (f) is simply the envelope of plot (h), it is therefore possible to reconstruct a single (averaged) heartbeat wave by taking the envelope of the spectrum of the PESD data with the majority of the breathing peaks removed, and then performing an IFFT on the spectrum. From Section 4.1.5 it can be seen that it would not be possible to separate the two sources (respiration and heartbeat) from another using pass-filters without losing information due to the overlapping frequency content of the two sources. For the purposes of this section however, it might not be necessary to have a complete heartbeat waveform as discussed in Section 5.3. However, the closer the matched filter coefficients are to a real heartbeat waveform, the more accurate the matched filter result will be.

, using interpolation (Matlab command: *interp1*). Interpolation is a method that finds the intermediate points in the desired data.

### 5.4.2 Designing the heartbeat estimator

The heartbeat estimator is designed as illustrated in the block diagram in Figure 5.17. A high-pass filter is used to remove the majority of the lower frequency breathing components from the signal. Next, the FFT is performed on the section of data. After performing the FFT on the data the envelope of the magnitude of the spectrum is taken. The process of envelope detection was done by first determining all the maximum points (defined as a point that has a greater value than the point to the immediate left and right of it) in the spectrum. Next, the local maxima of these points were determined by finding the maximum points with a value greater than the maximum point to the immediate left and right of it. Interpolation was then used to directly link these local maximum points, but with the same number of data

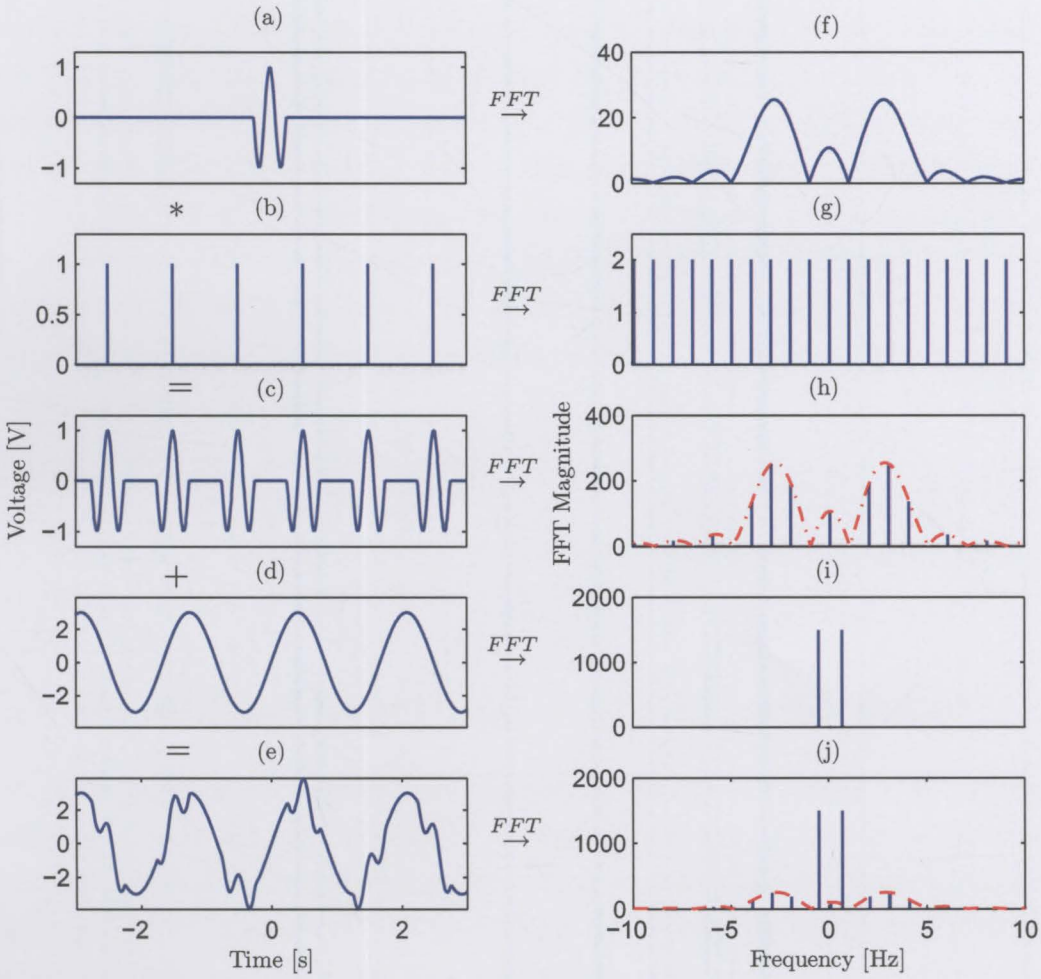


**Figure 5.16:** *Simplified model of PESD signal composition. Plots (a)-(e) are the time plots and (f)-(j) are the corresponding FFT. A single heartbeat (a) is convolved with impulse train (b) to obtain heartbeat sequence (c). This is added to sinusoidal respiration (d) to obtain the simulated result in (e).*

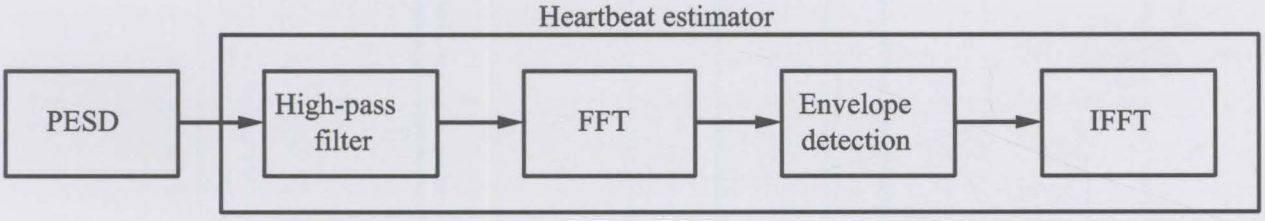


**Figure 5.17:** *Block diagram of the proposed heartbeat estimator.*

points as the original spectrum. Interpolation is a method that finds the intermediate points in the desired data and the Matlab command *interp1* was used to perform interpolation. Also, only the one side of the spectrum is used to determine the envelope so in order to reconstruct the double-sided spectrum again, the inverse of the enveloped spectrum is added to the end of the original enveloped data. The signal is however complex in nature, so reconstruction is achieved by calculating the complex conjugate of the envelope signal and adding it to the end of it in a reversed order (back-to-front) way. During the FFT however, the magnitude and phase of the signal get separated and the envelope is performed on the magnitude while the phase information remains unchanged. Reconstruction of the complete signal is then performed using:

$$X_n = |X_n| e^{j\angle X_n} \tag{5.5}$$

After this the IFFT is taken to obtain a time domain version of the signal again which is fed into the matched filter as coefficients.

## 5.5 Determining heartbeat from filtered data

A matched filter is designed to maximize the output energy of a signal that corresponds to a known signal $s(t)$ (as discussed earlier). An example of this is shown in Figure 5.18 (b). Notice how the matched filter output energy is maximized at the positions where the heartbeats are situated (large peaks in plot (b)). Plot (a) reveals the single heartbeat obtained from the estimation filter step which was fed into the matched filter and used to detect the other heartbeats.

Figure 5.19 (a) shows the output from a matched filter that has insertions as well as deletions visible together with the correct heartbeat peaks. Peaks that are larger than a specified threshold are seen as heartbeats. An impulse sequence of heartbeats is then created by setting the position of each of the detected peaks to one in a separate vector while the rest of the positions are set to zero. Figure 5.19 (b) shows such a set of impulses created from the matched filter output in plot (a). This impulse version of a sequence of heartbeats is then fed into the heart rate estimation phase where the histogram analysis is performed to determine the properties of the heart rate (Section 5.1). The threshold used for peak detection is dependent on the average size of the peaks contained in the signal. For this project it was chosen to be 70 % of the average size. The threshold is used to which all the maximum points of the signal are compared relative to the next minimum point. So if the difference between a maximum followed by a minimum exceeds the threshold value then that peak is seen as a potential heartbeat.

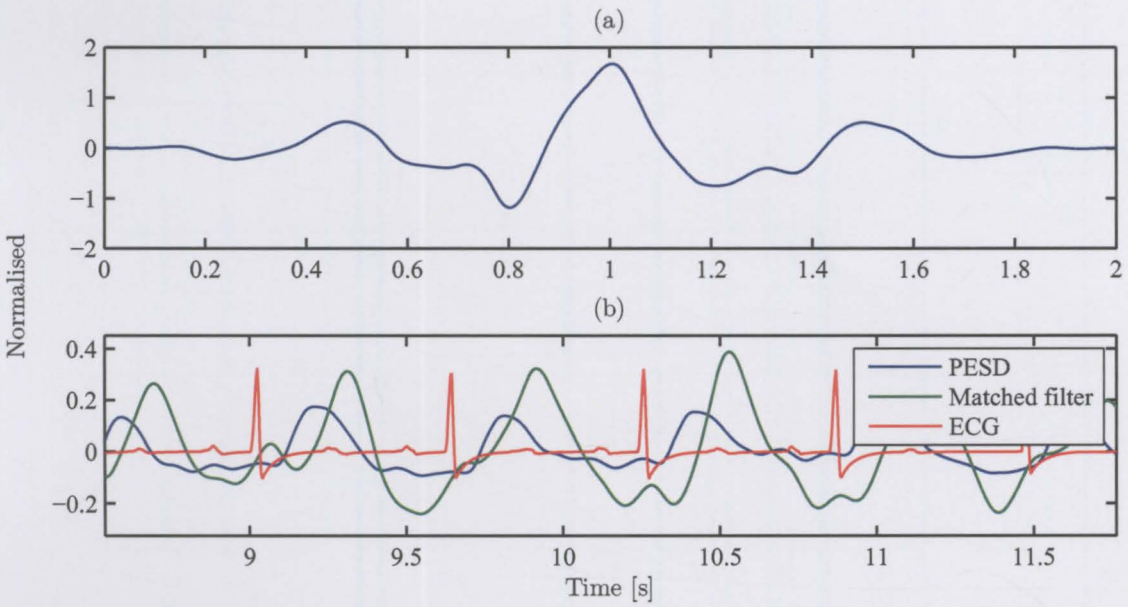


**Figure 5.18:** *Output from the estimation filter (a) revealing only a single heartbeat which is used by the matched filter to detect other heartbeats. Plot (b) shows a PESD signal containing only heartbeats (no breathing), its ECG and also the corresponding matched filter output obtained by using the heartbeat signal in (a).*

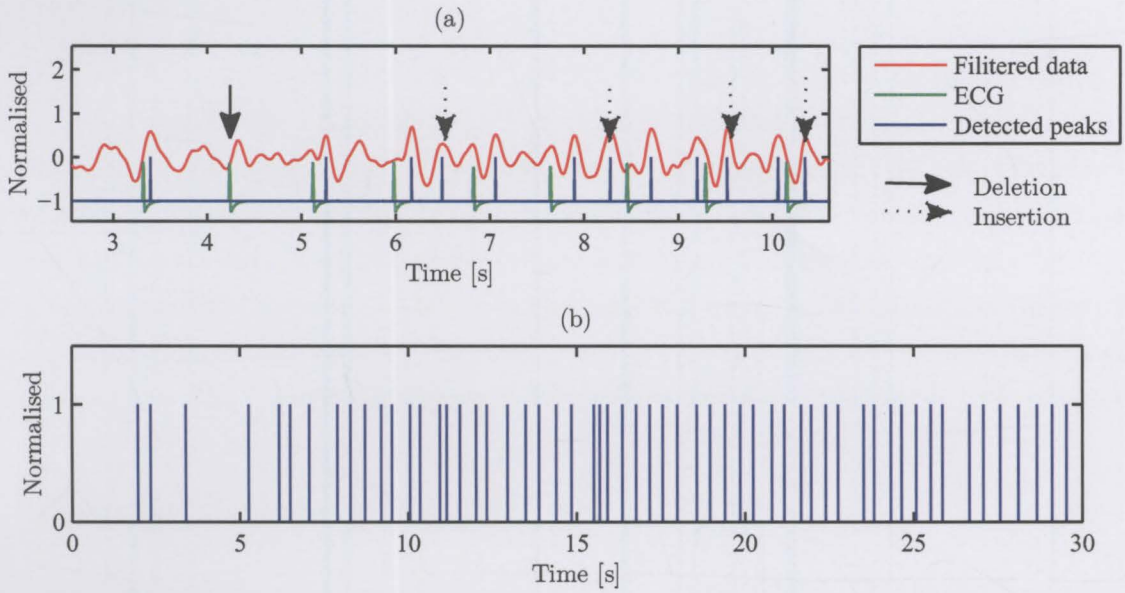


**Figure 5.19:** *Example of the (a) output from matched filter with peak detection. Plot (b) shows the impulse version of the heartbeat peaks after peak detection was performed on the matched filter output.*

# Chapter 6

# Results

In this chapter, examples are given of the output from the heartbeat estimator using data containing only heartbeat information. The output for data containing respiration and heartbeats will not be shown since there is no source of reference to compare the result to. The system as a whole was tested using data containing only heartbeats, data containing respiration and heartbeat, and also infant data containing respiration and heartbeat. The accuracy of the system is summarized in tables and the error is calculated in terms of the number of beat differences between the calculated heart rate, and the actual heart rate as measured using an ECG. Explanations and discussions are also included in this chapter.

## 6.1 Analysis using simulated data

The matched filter process was initially tested using simulated data. Simulated data provides a simple signal that can consist only of the two present sources with no noise present. This allows for the system to be tested without the presence of noise.

A signal was generated with a heart rate of 100 bpm and a breathing frequency of 0.5 Hz. For the construction of the heartbeats, a sinusoidal wave of 5 Hz was used and a single period from this signal was selected as a single heartbeat. The heartbeat was then convolved with a impulse train with the spacing between the impulses corresponding to that of a heart rate of 100 bpm. To create a more realistic heartbeat signal, variation in the heart rate is included by multiplying the spacing between the impulses in the train by a random value which ranges between $-0.12\ s$ and $+0.12\ s$. This signal hence is just a much simpler form of a typical signal obtained from the PESD, due to the absence of noise and disturbances.

Figure 6.1 shows the construction of the simulated signal. Plot (a) shows the sinusoidal wave representing the respiration while in plot (b) one can see the simulated heartbeat. These two are then combined to create the complete signal shown in plot (c).

The simulated signal was then used as input to the matched filter system. Figure 6.2 (a)

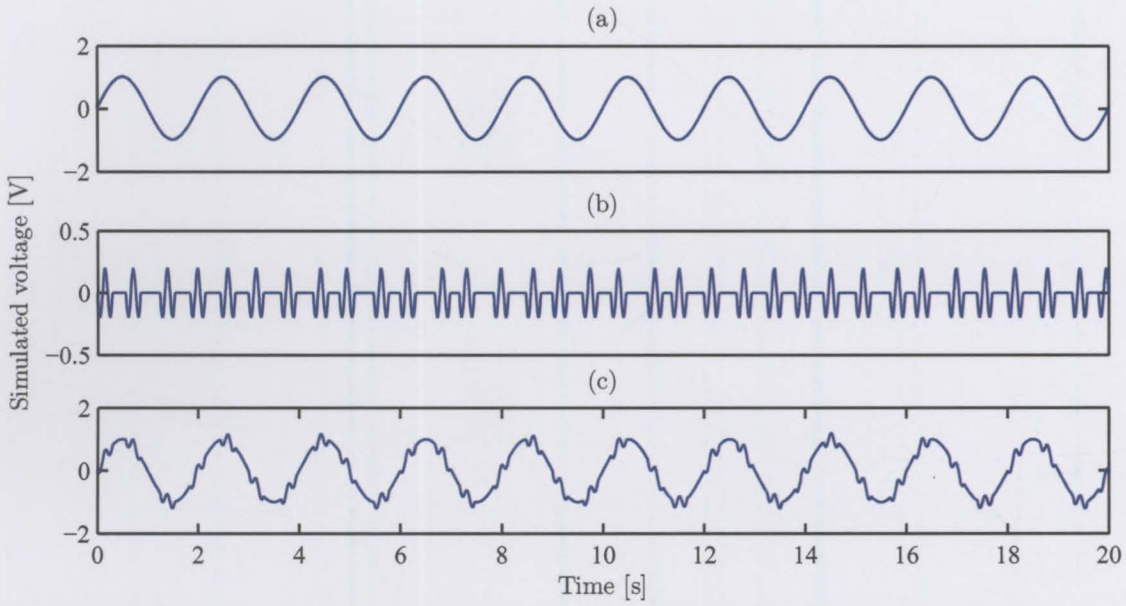


**Figure 6.1:** *Respiration is simulated using a sinusoidal wave of frequency $f = 0.5$ Hz in (a). The heartbeat sequence (b) was created by correlating a single sinusoidal period of frequency $f = 5$ Hz with an impulse train. The above two were then added to create the complete simulated signal in (c).*

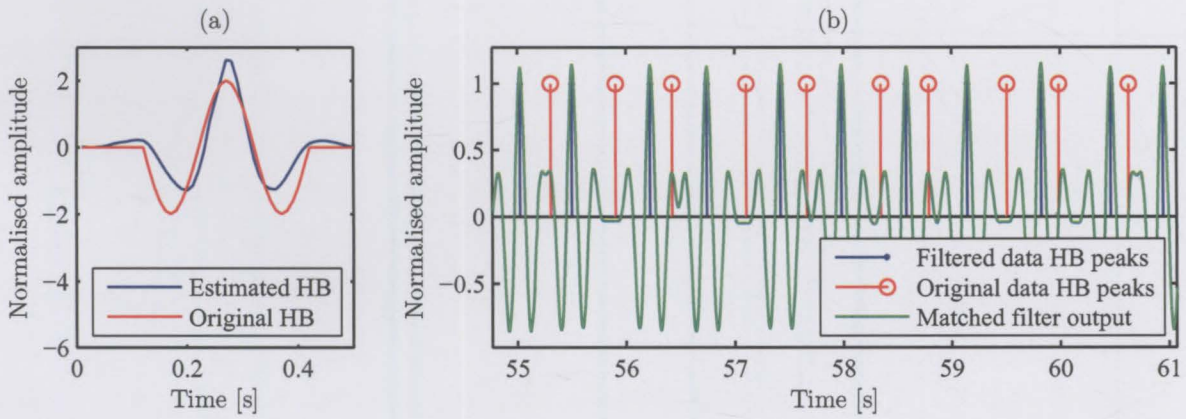


**Figure 6.2:** *Plot (a) shows a single simulated heartbeat as well as the estimated heartbeat as obtained from the estimation filter. Plot (b) shows an impulse version of the original heartbeat peaks as well as the detected heartbeat peaks after matched filtering was performed. The matched filter output is also shown.*

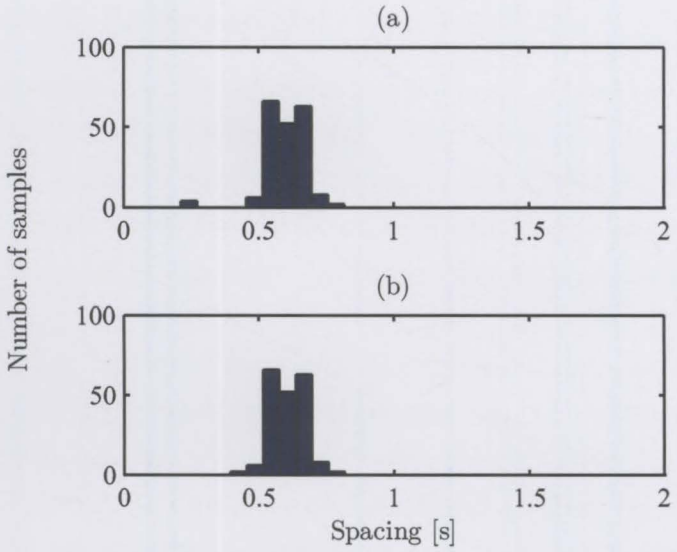


**Figure 6.3:** *Histogram of (a) matched filtered simulated data and (b) the original simulated data.*

shows the estimated heartbeat obtained from the output of the estimation filter. The small difference between the estimated heartbeat and the original heartbeat can be ascribed to taking the envelope of the FFT of the signal (as discussed previously). The frequency content of the estimated and original heartbeat is within the same range, but due to the envelope, the magnitudes of their frequency components are different. Figure 6.2 (b) shows the output from the matched filter with the identified peaks indicated by impulses. From plot (b) one can see that the spacings between impulses representing the detected heartbeats are similar in size to the spacings between the impulses representing the positions where the simulated heartbeats are (original data). The equal size in spacings between peaks are confirmed in the histogram plots of Figure 6.3 with the histogram plots of the original and matched filtered signal being almost identical.

## 6.2 Analysis using adult data with only heartbeats

Analysis of PESD data is first performed with data that only contains cardiovascular information. This allows for the effectiveness of the filtering and heartbeat extraction procedures to be examined on only the heartbeat before moving on to data with respiration and heartbeats. The presence of respiration in the signal is expected to cause a decreased accuracy of heartbeat extraction due to the overlapping frequencies.

### 6.2.1 Estimation filter output

The accuracy of the output of the estimation filter plays a big role in the matched filtering process. In the previous discussions it was stated that the heart rate changes and the heartbeat waveform constantly changes in shape in the PESD signal. The estimation filter therefore estimates an averaged version of a single heartbeat, which will therefore not look like any one specific heartbeat waveform, but rather like a combination of all of the heartbeat waveforms.

The plots on the left in Figure 6.4 shows the output obtained from the estimation filter for numerous data sets. These estimated heartbeats can be compared to the PESD recorded heartbeats in the plots on the right in the same figure to see how closely the estimated heartbeat resembles the original heartbeats. In all these examples clear comparisons can be made and similarities be identified between the estimated and original heartbeats.

### 6.2.2 Accuracy of heart rate detection using the matched filter

The accuracy of the heart rate detection process is measured relative to the heart rate information obtained from the ECG recordings. For the next experiment, seven sets of data obtained from seven different patients were used. These data sets consist only of cardiovascular information. The subject's recordings are labeled as *Subject1* to *Subject7*.

The first part of this experiment aims to examine the accuracy of matched filtering by studying the output after peak detection was performed to recognize the heartbeats. Heartbeat detection was performed on all seven data sets as well as for two other noise sources. The two noise sources consist solely of brown noise and white noise, consecutively.

The histogram plots for the spacing between peaks for the above-mentioned data sets are shown in Figure 6.5. The plots in this figure are grouped together in twos. The top one of the two is the histogram for the spacing between detected peaks from the PESD data while the bottom plot is the histogram of the ECG peaks. Plot (a) however, shows the histogram plot obtained after performing matched filtering and peak detection on the two noise sources. The first plot in plot (a) is for brown noise while the second plot is for the white noise. By comparing these two histograms in (a) to those of the subjects (plots (b)-(h)) in Figure 6.5, it can clearly be seen that the noise sources creates a much wider peak in the histogram plot, which allows for them to clearly be distinguished from the data that contains heartbeats.

The histogram plots of the detected heartbeats from the PESD data are very similar to that of the ECG. As reasoned before, the closer the histograms of the PESD data are to that of the ECG, the more accurate the filter and detection method is. The results in these plots suggest that the matched filter technique works well for detecting the heartbeats from a source that does not contain any respiration artefacts.

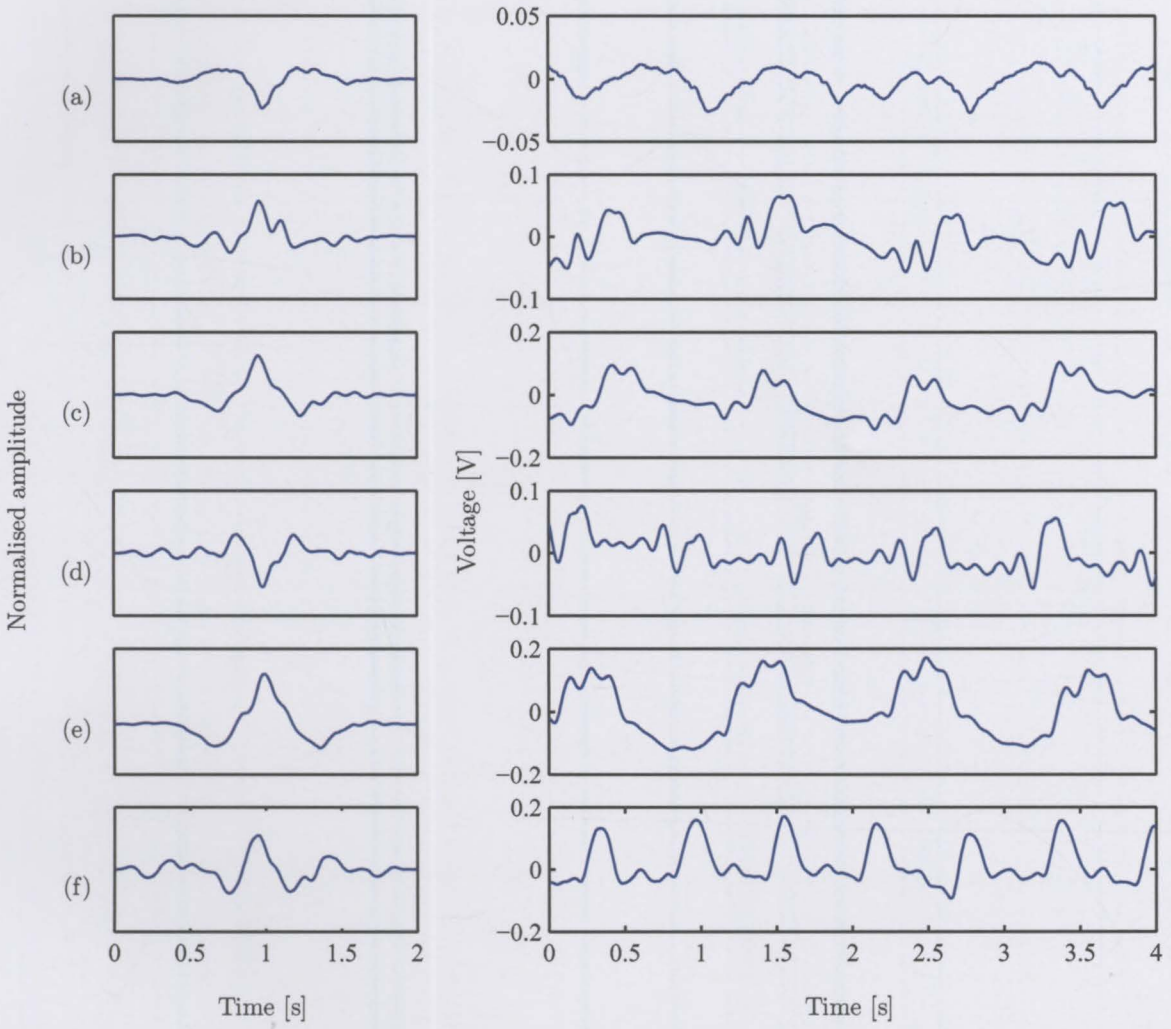


**Figure 6.4:** *Plots on the left shows the estimated heartbeat as obtained from the output of the estimation filter for data sets recorded on numerous subjects. The plots to the right show the actual heartbeats for the subjects.*

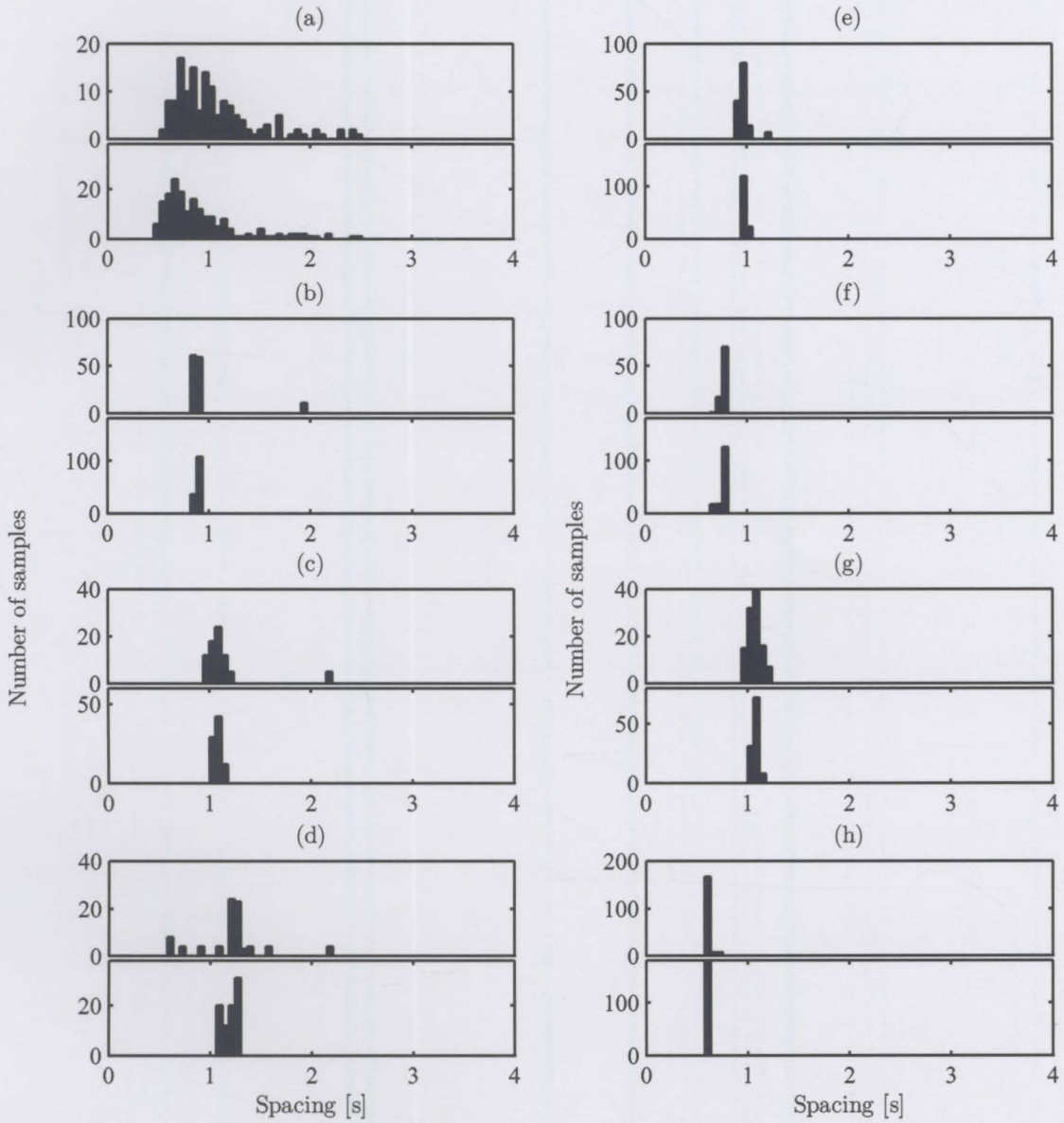


**Figure 6.5:** *The two plots in (a) contains the histogram plots for brown noise and white noise consecutively after performing matched filtering. The remaining plots (b)-(h) show the histogram plot for the seven subjects (Subjects 1-7) after performing matched filtering and peak detection. The top plot in each of (b)-(h) is the histogram of the measured data while the bottom plot is the histogram of the ECG.*

These histogram plots however, provide a visual way of examining the effectiveness of the matched filter process. Next, the information contained in the histogram plots will be converted to numerical values in order to exactly determine the accuracy (or error) of the matched filter detection method.

Firstly, the spacings between consecutive peaks provide information regarding the heart rate of a subject. Instead of taking the average spacing over the total duration, windowing is performed on the data. A window was selected to be 15 s long (discussed in Section 5.3.1). The average heart rate was then calculated for this window. Next, the window was shifted 100 samples (1 s) forward and the average heart rate calculated again for the new window. This process was repeated until the window reached the end of the data set. This process resulted in a series of averaged heart rates. The same was done to the ECG so that the heart rate from the PESD data can be compared to that of the ECG. The rest of the experiments discussed in this chapter, were conducted in the same manner, but with different data sets.

The two methods used for averaging the heart rate were the *mean* and *median*. The error values (summarized in Table 6.1) were calculated by subtracting the PESD result from the ECG result and therefore resulting in a heart rate error measured in beats per minute (bpm). The error for each window was calculated and the average for these errors for each subject is summarized in the columns labelled *Avg error* in Table 6.1. The maximum error calculated for a window for each subject is also shown in the table under the column *Max error*.

**Table 6.1:** *Maximum and average error (in bpm) of measured heartbeat (from PESD data containing only heartbeat) relative to ECG measurement.*

| Data sets | Mean | | Median | |
|---|---|---|---|---|
| | Max error [bpm] | Avg error [bpm] | Max error [bpm] | Avg error [bpm] |
| Subject1 | 10.59 | 5.08 | 2.10 | 1.09 |
| Subject2 | 4.81 | 3.47 | 0.51 | 0.17 |
| Subject3 | 6.48 | 4.50 | 5.33 | 2.17 |
| Subject4 | 1.50 | 0.53 | 2.06 | 0.79 |
| Subject5 | 3.80 | 3.24 | 2.39 | 2.39 |
| Subject6 | 0.74 | 0.21 | 0.42 | 0.21 |
| Subject7 | 0.65 | 0.22 | 1.94 | 1.87 |
| **Average** | 4.08 | 2.46 | 2.11 | 1.24 |

Four out of the seven subjects revealed a larger average error using the mean to perform

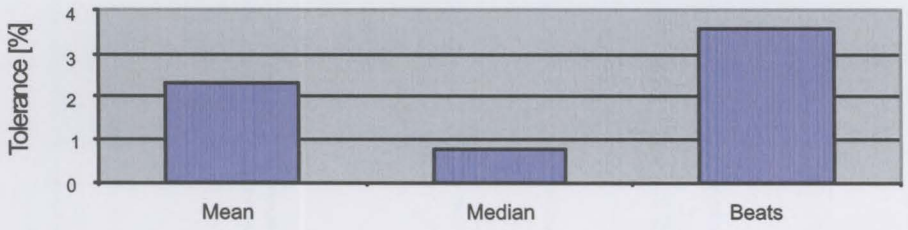


**Figure 6.6:** *A bar plot showing the average errors as a percentage of the ECG values for adult cardiovascular data.*

the average heart rate calculation and five out of the seven subjects had a larger maximum error using mean to perform the average heart rate calculation. Also, the total average heart rate calculated using the median, has an error of half that of the mean for both maximum and average error. Figure 6.6 shows a bar plot of the average error achieved for the different subjects. The error is expressed as a percentage of the ECG result and is calculated as the difference between the PESD result and the ECG result. The third bar shows the percentage error for the number of beats detected after matched filtering.

From the above results it can be seen that using the median to calculate the average heart rate is more accurate compared to using the mean. Other more advance statistical approaches are also possible in determining the average heart rate, but is not covered in this report. For the detailed statistical values of each subject, refer to Appendix B.1.

## 6.3 Analysis using adult data containing respiration and heartbeats

The same experiments described in the previous section were performed on the data which contains respiration as well as heart information. For this experiment, eight subjects were recorded for a duration of three minutes each. The data was then filtered to remove the DC offset and the majority of the lower frequency breathing. Table 6.2 shows the error margins achieved while using mean and median consecutively to determine the average heart rate for each subject. As in the previous section's experiment, to obtain the values in this table, a window of width $t = 15$ s was used. The column labelled *Avg error* contains the average value for the error obtained for each window, whereas the columns *Max error* contains the largest error value achieved for a single window.

For this experiment the error values for mean and median are very close to one another, but much larger than for the experiment where only heart information is present in the test

**Table 6.2:** *Maximum and average error (in bpm) of measured heartbeat (from PESD data containing respiration and heartbeats) relative to ECG measurement.*

| Data sets | Mean | | Median | |
|---|---|---|---|---|
| | Max error [bpm] | Avg error [bpm] | Max error [bpm] | Avg error [bpm] |
| Subject1 | 12.82 | 4.58 | 16.54 | 4.65 |
| Subject2 | 19.65 | 5.52 | 9.98 | 2.70 |
| Subject3 | 12.69 | 3.55 | 14.43 | 2.75 |
| Subject4 | 11.21 | 2.83 | 11.34 | 4.33 |
| Subject5 | 14.11 | 3.24 | 11.99 | 3.44 |
| Subject6 | 11.72 | 3.15 | 15.93 | 4.35 |
| Subject7 | 11.31 | 4.57 | 11.32 | 3.06 |
| **Average** | 13.36 | 3.88 | 13.08 | 3.62 |

data.

Figure 6.7 shows the error obtained for the statistics of the matched filter output as a percentage of the ECG statistics. In this figure, once again, it can be seen that median provides a better result for calculating the heart rate. Here it is shown that the error obtained is less than 5 % of the actual ECG-determined value (3.62 bpm error with an ECG determined heart rate of 75 bpm). The number of heartbeats detected, however, shows an error of almost 12 %. A closer look at the number of heartbeats detected reveals that this large error is due to many deletions being present in the signal. From this it is evident that even in the presence of many deletions, the heart rate can still be detected accurately.

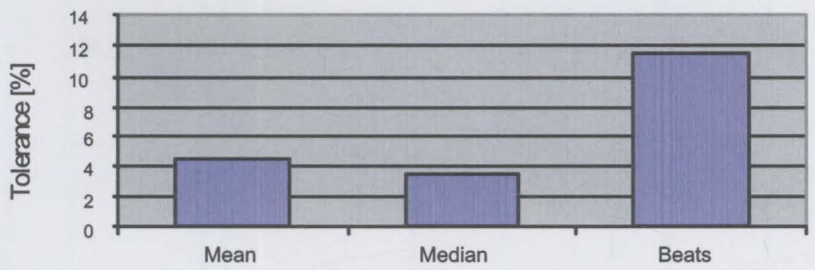


**Figure 6.7:** *A bar plot showing the average errors as a percentage of the ECG values for adult data containing respiration and heartbeats.*

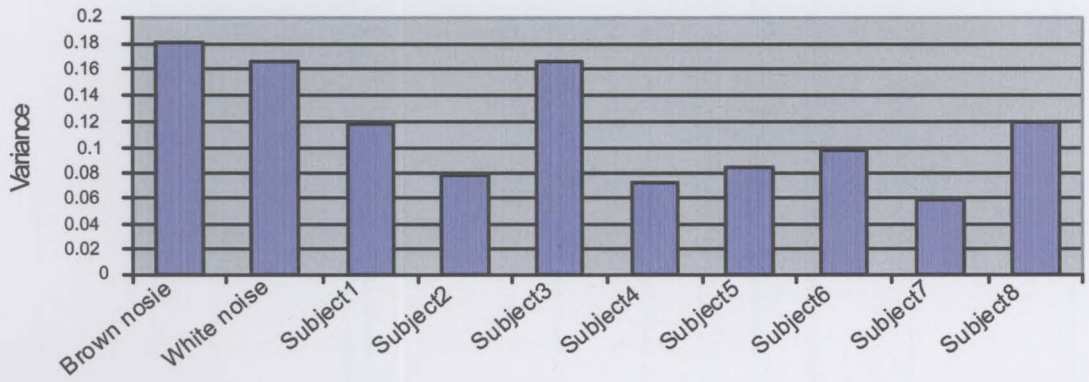


**Figure 6.8:** *A bar plot showing the variance values after matched filtering has been performed on adult data containing respiration and heartbeats.*

The variance is a measure of the width of a peak and is used to separate noise from heartbeat data. Noise tends to have a much larger variance (i.e. a wider histogram peak). Figure 6.8 shows a bar plot for the variance values obtained for each subject, and also for the different noise sources. In this figure it can be seen that the variance calculated for the noise sources is much larger compared to the data that contains heartbeats. The only exception is *Subject3*. For this subject, only 117 out of 191 heartbeats were detected successfully. An investigation was done in order to understand why this data set yielded such poor results, and it was found that the recorded signal had numerous large artefacts, possibly due to physical movement while the recording was in progress.

## 6.4 Analysis using infant data containing respiration and heartbeat

The experiments presented here were conducted in the same manner as the experiments presented in Section 6.2. In this case however, numerous data sets were recorded from three infants. The infants were sleeping while recordings were done. This minimized any movement artefacts that will be caused by the infant while awake.

From the table showing the maximum and average errors calculated for the average heart rate (Table 6.3), it can be seen that the error obtained for infants using the matched filter approach is much larger than the error values found with adults. As in the previous experiments, the median method produces much better results for estimating the heart rate. With an actual heart rate of $\pm 75$ bpm, an error of 9.7 bpm is equal to approximately 13 %

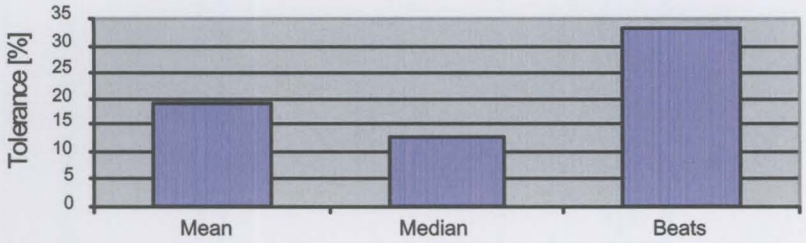


**Figure 6.9:** *A bar plot showing the average errors as a percentage of the ECG-determined values for infant data containing respiration and heartbeats.*

of the actual heart rate.

**Table 6.3:** *Maximum and average error (in bpm) of measured heartbeat (from infant PESD data containing respiration and heartbeats) relative to the ECG measurements.*

| Data sets | Mean | | Median | |
|---|---|---|---|---|
| | Max error [bpm] | Avg error [bpm] | Max error [bpm] | Avg error [bpm] |
| Subject1-1 | 14.382 | 8.549 | 11.823 | 3.749 |
| Subject1-2 | 16.113 | 7.636 | 7.559 | 2.746 |
| Subject1-3 | 20.396 | 16.418 | 17.857 | 13.201 |
| Subject1-4 | 17.208 | 6.868 | 21.808 | 6.400 |
| Subject1-5 | 15.774 | 8.759 | 5.503 | 3.376 |
| Subject2-1 | 20.905 | 12.923 | 11.988 | 6.874 |
| Subject2-2 | 26.500 | 17.266 | 22.906 | 14.092 |
| Subject3-1 | 26.269 | 20.352 | 22.584 | 14.835 |
| Subject3-2 | 25.929 | 18.130 | 20.946 | 14.244 |
| Subject3-3 | 19.083 | 16.573 | 19.455 | 17.213 |
| **Average** | 20.245 | 13.345 | 16.243 | 9.673 |

As for the previous experiments, the average error values (relative to the ECG measurement) of the statistical properties for all the data sets is shown as a bar plot in Figure 6.9. The number of counted heartbeats, however, has a 33 % error. After a study of the data sets, it was found that this is due to deletions present in the signals. Out of a total of 682 heartbeats present in all the data sets, only 456 were detected successfully.

The variance of the matched filtered data shows that there exists a clear distinction between noise and real data. Figure 6.10 shows a bar plot containing the variance values

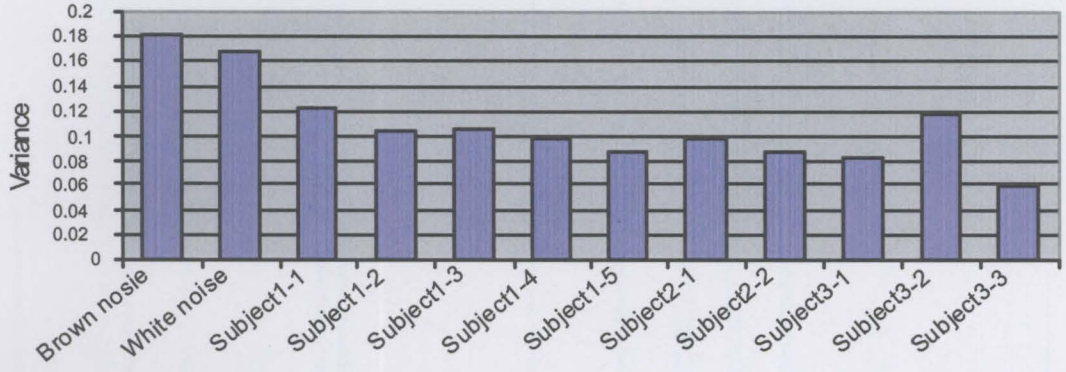


**Figure 6.10:** *A bar plot showing the variance values after matched filtering has been performed on infant data containing respiration and heartbeats.*

obtained for the different data sets. From this figure it can be seen that the noise data causes a significantly larger variance compared to data that contains a heartbeat.

## 6.5 Remarks

From the results presented in this chapter on the three main data sets, it was found that the median produces the best estimation of the heart rate. A decrease in accuracy was noted between data containing only cardiovascular information and data containing both respiratory as well as cardiovascular information. Similarly, a decrease in accuracy was noted between the results from adult data to the results obtained from infant data. This was expected, however, since the respiration artefacts in the infant data relative to the heartbeats is much stronger compared to the relationship in the adult data.

# Chapter 7

# Conclusions

## 7.1 Contribution of research

In this project, a new technique was investigated by which heartbeats could be detected using a piezo-electric sensor rather than the conventional electrocardiograph (ECG).

This project contributes to the addition of a heartbeat detection feature to an existing breathing monitor. Matched filter coefficients were estimated from heartbeat data and it was successfully demonstrated that the heartbeat information can be compressed into a single pulse.

A matched filter technique was used to statistically determine heartbeat spread and heart rate. Statistical methods were applied on the matched filtering results, through which it was attempted to enhance the heartbeat pulses to recognisable heartbeats. The heartbeat energy that is spread over time is condensed by compressing the information. Statistical analysis was used to decide whether a heartbeat is present and what the heart rate is, rather than identifying each individual heartbeat step-by-step and then attempting to use a complex decision-making process. This was done by studying the statistical properties of a single window of data, and then deciding whether heartbeat was present and what the heart rate was.

## 7.2 Problems to be addressed in future work

The handling of insertions and deletions during the heart rate calculation, was minimized. When a double Gaussian distribution is obtained with the second peak being at double the time instance of the first peak, then the second peak is a deletion peak. This deletion peak, which still contains information regarding the heartbeat, was recognised by the methods presented in this report, but was ignored in the calculations. This in turn worsens the

statistical properties of the data. A technique could be implemented that recognises the deletion peak and combines its statistical properties with that of the correct heartbeat peak.

There is also room for refining the matched filter technique. The principles of the matched filter technique were shown to work, but the way in which the heartbeat estimation approximates a heartbeat waveform (which serves as input to the matched filter) still requires improvement. The heartbeat estimation process takes the envelope of the FFT to estimate a single heartbeat, if respiration is present in the signal after filtering, then the matched filter coefficients will also contain respiration artefacts. That will result in respiration being part of the extracted "heartbeat" signal.

It is recommended that a future study re-investigates wavelet analysis to extract heartbeat information from the piezo-electric sensor. The initial experiments showed that wavelets provided good results, except for the fact that the heart rate information was spread across different scales for the different subjects. Although wavelet analysis is more computationally intensive, wavelets can also be approached in the same way as the matched filter technique. Wavelet analysis can be studied while using a heartbeat estimation to obtain a single heartbeat to serve as wavelet for the process.

Although this project was limited to developing a heartbeat detection system without changing the position at which the device is located, further studies is recommended on other possible locations for recording the data. This includes using a separate piezo-electric sensor connected to a belt that might be connected to the wrist or chest. Experimentation with different sensors, other than a piezo-electric sensor, is also suggested in order to determine the presence of heartbeat in a small battery-operated device such as the one used in this project.

## 7.3 Final remarks

The proposed system yielded an accuracy of less than 2 % error using adult data containing only heartbeats, 5 % using adult data containing respiration and heartbeats, and 13 % using infant data containing respiration and breathing. Based on the objectives of this project and the results achieved, the proposed methods shows promise for enhancing the capabilities of the breathing monitor and could serve to improve the reliability and sensitivity of such a monitor.

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# Appendix A

# Other related research and experiments

## A.1 Effect of Sensor Placement

Although one of the requirements is that the PESD position must remain the same, this section takes a brief look at the effect of the sensor placement on the signal obtained from the PESD, in order to determine if a change in the position of the sensor might help to more easily identify the heartbeat.
For this experiment, the PESD was placed at three different locations on one subject. He was asked to hold his breath at each location so that only the cardiovascular data can be recorded. The three locations are indicated in Figure A.1 and will be referred to as *location 1*, *location 2* and *location 3*. The first two positions allows for the PESD to maintain its original functionality since they both allow for the PESD to be connected to the belt of the subject (as it would be when connected to the nappy of a baby). The third position is just

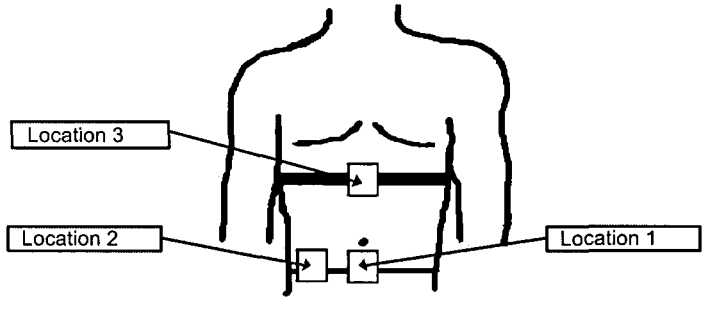


**Figure A.1:** *Effect of sensor placement was tested by making recordings at these three locations.*

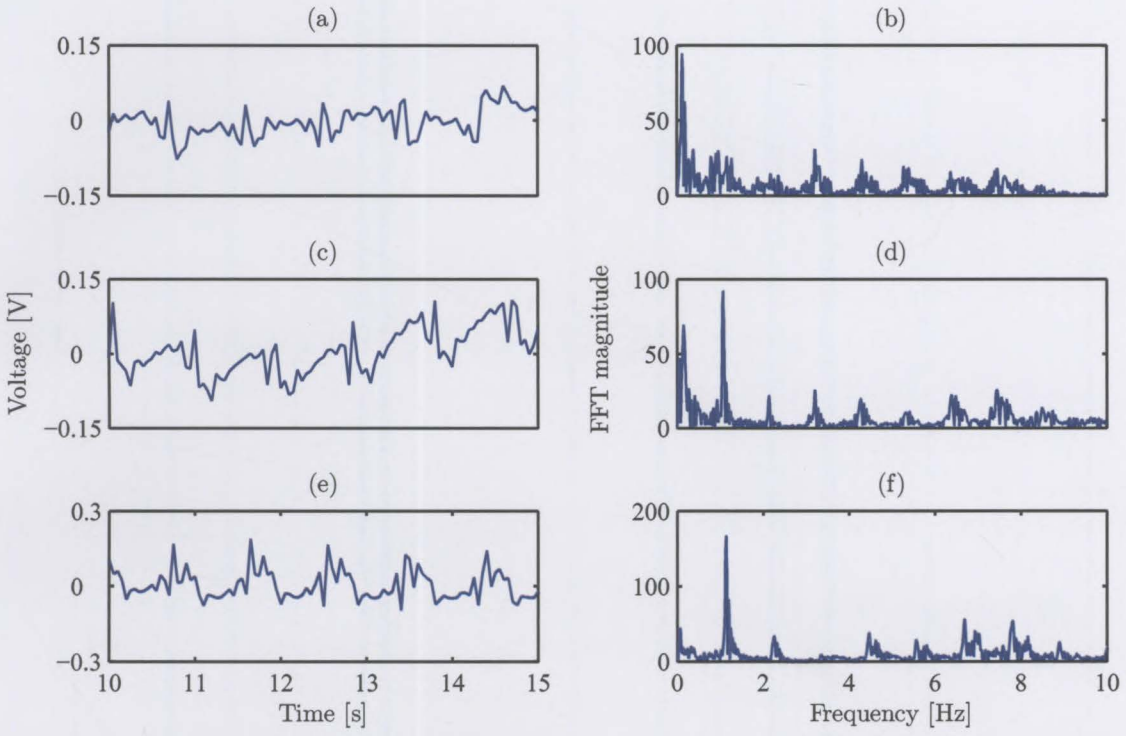


**Figure A.2:** *Data obtained for three recordings ((a),(c) and (e)) made at different locations (location 1, 2 and 3 consecutively) with their corresponding frequency plots ((b),(d) and (f)).*

above the belly where less breathing (movement of the stomach) is present, but just below the rib cage in order to detect the heartbeat. This location was selected because it was very close to the heart and it was believed that the heartbeat might be stronger or more clearly visible at this location.

The signals recorded with the PESD at these three locations are shown in Figure A.2 as plots (a), (c) and (e) with their corresponding frequency plots to the right of each (plots (b), (d) and (f)). The fundamental frequency as well as their harmonics can be identified in all three the frequency plots. However, the fundamental frequency in the first frequency plot (*location 1*) is less prominent, while that of the third plot (*location 3*) is much stronger than the other two. The frequency plots of the first two locations reveals stronger lower frequency components and their time domain plots shows that the recorded heartbeat signals are smaller than the one recorded at *location 3*. It appears, therefore, that recordings made at *location 3* might provide stronger heartbeat information.

# Appendix B

# More detailed results

## B.1 Adult data containing cardiovascular information

The result obtained for calculating the average heart rate using the *median* is shown in Figure B.1 and the result when using the *mean* is shown in Figure B.2. The results for *Subjects1* to *Subject7* is shown as Plots (a)-(g) in both figures.
Some important characteristics for determining heart rate properties are shown in Table B.1. The variance calculated in Table B.1 confirms the previous observation that the

**Table B.1:** *Results of statistical analysis using heartbeat-only data.*

| Data sets | ECG data | | | PESD data | | | |
|---|---|---|---|---|---|---|---|
| | Mean | Med | Beats | Mean | Med | Var | Beats |
| Brown noise | N/A | N/A | N/A | 55.82 | 61.22 | 0.181 | 145 |
| White noise | N/A | N/A | N/A | 64.93 | 75.47 | 0.167 | 182 |
| Subject1 | 67.05 | 67.26 | 143 | 61.97 | 67.57 | 0.093 | 131 |
| Subject2 | 55.80 | 55.35 | 83 | 52.45 | 55.56 | 0.079 | 76 |
| Subject3 | 49.97 | 48.86 | 83 | 50.02 | 49.02 | 0.109 | 82 |
| Subject4 | 61.79 | 62.24 | 143 | 61.90 | 63.03 | 0.005 | 141 |
| Subject5 | 77.80 | 76.14 | 161 | 79.41 | 78.53 | 0.001 | 88 |
| Subject6 | 55.88 | 55.97 | 111 | 55.94 | 55.97 | 0.004 | 110 |
| Subject7 | 97.59 | 97.40 | 183 | 97.71 | 99.34 | 0.001 | 181 |

histogram peaks for the noise sources are much wider than that of the PESD data. By comparing the counted beats in Table B.1 under the column *Beats*, one can see that the number of ECG peaks are in most cases almost equal to the amount of PESD peaks. This confirms the effectiveness of detecting heartbeat peaks using the approach of matched

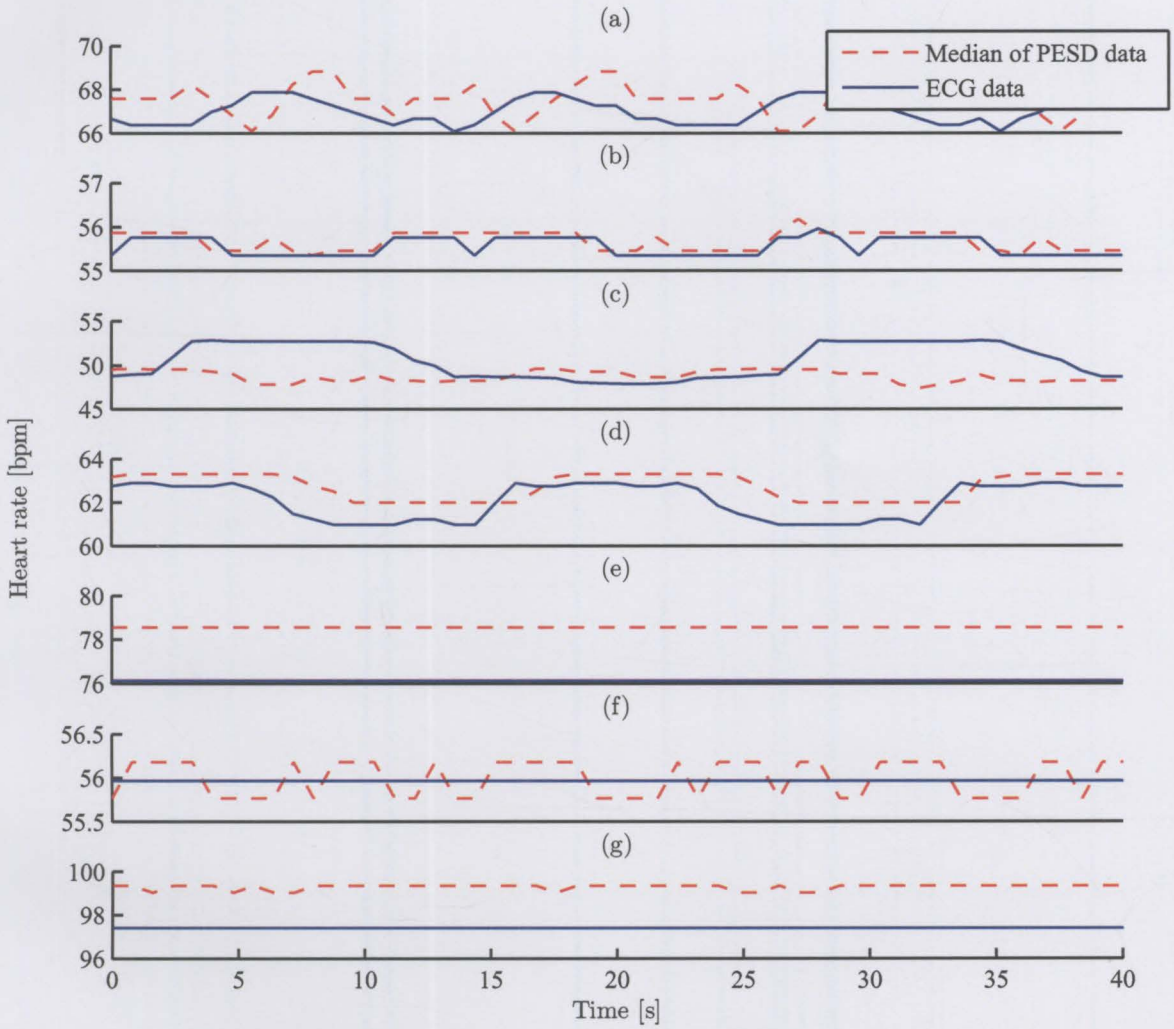


**Figure B.1:** *Plots (a)-(g) shows the heart rates for the seven subjects (Subjects 1-7) as calculated using the median of the data for the ECG versus the heart rate as calculated the measured PESD data.*

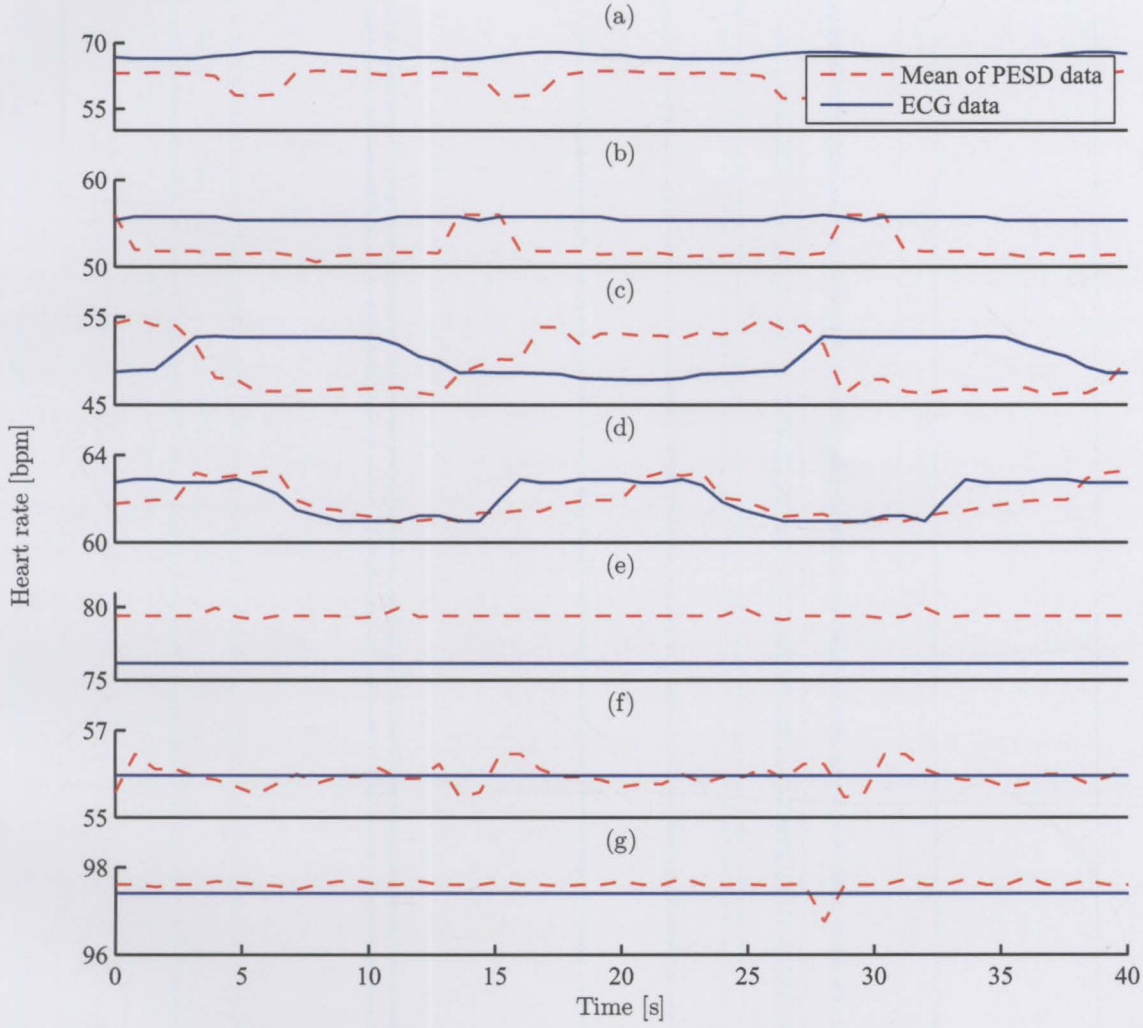


**Figure B.2:** *Plots (a)-(g) shows the heart rates for the seven subjects (Subjects 1-7) as calculated using the mean of the data for the ECG versus the heart rate as calculated the measured PESD data.*

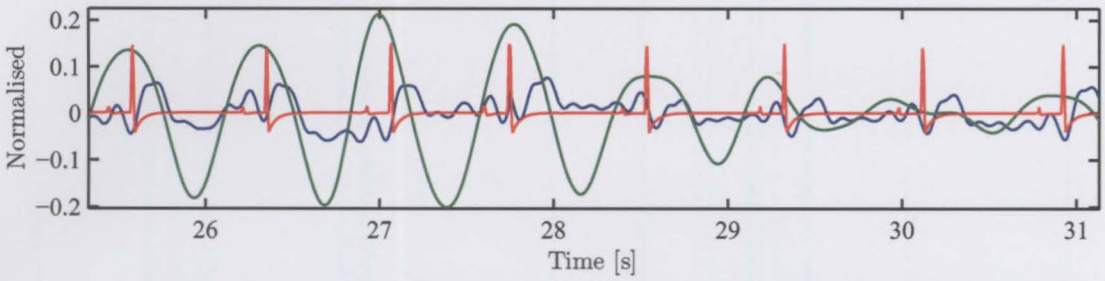


**Figure B.3:** *Example of a matched filter output with sudden drop in peak size.*

filtering. The one exception is *Subject5* where the ECG beat count delivers 161 beats whereas the PESD beat count delivers a mere 88 beats. The big difference in the number of beats is due to the presence of many deletions after the peak detection phase. Note that the average heart rate according to the mean and median for the PESD data still achieves an accuracy of ±2 bpm compared to that of the ECG data. This finding confirms the effectiveness of the procedure which uses heartbeat spacings to determine the presence of the actual heart rate.

The question that arises however is why the deletions did not result in a deletion peak on the histogram plot for Subject5 in Figure 6.5. After closer inspection of the matched filter output, it was found that the shape of the heartbeat waveform for Subject5 changed over time in such a way that the matched filter produced very small peaks for certain heartbeats which lasted for durations greater than four seconds. Figure B.3 reveals one such section where the matched filter output becomes very small for a long duration and therefore not producing many small deletions, but rather one very large spacing of $T > 4$ s which is beyond the axis limit for the histogram plot.

## B.2 Adult data containing cardiovascular and respiratory information

Figure B.4 shows the histogram plots after matched filtering was performed on the eight recorded subjects. The plots are grouped together in twos with the top histogram plot being that of the measured data while the bottom one is the histogram plot of the ECG. The closer the two plots are to one another, the more accurate the result is.

In these plots it can be seen that the width of the measured histogram plots are significantly larger than those obtained from the previous experiments (using only

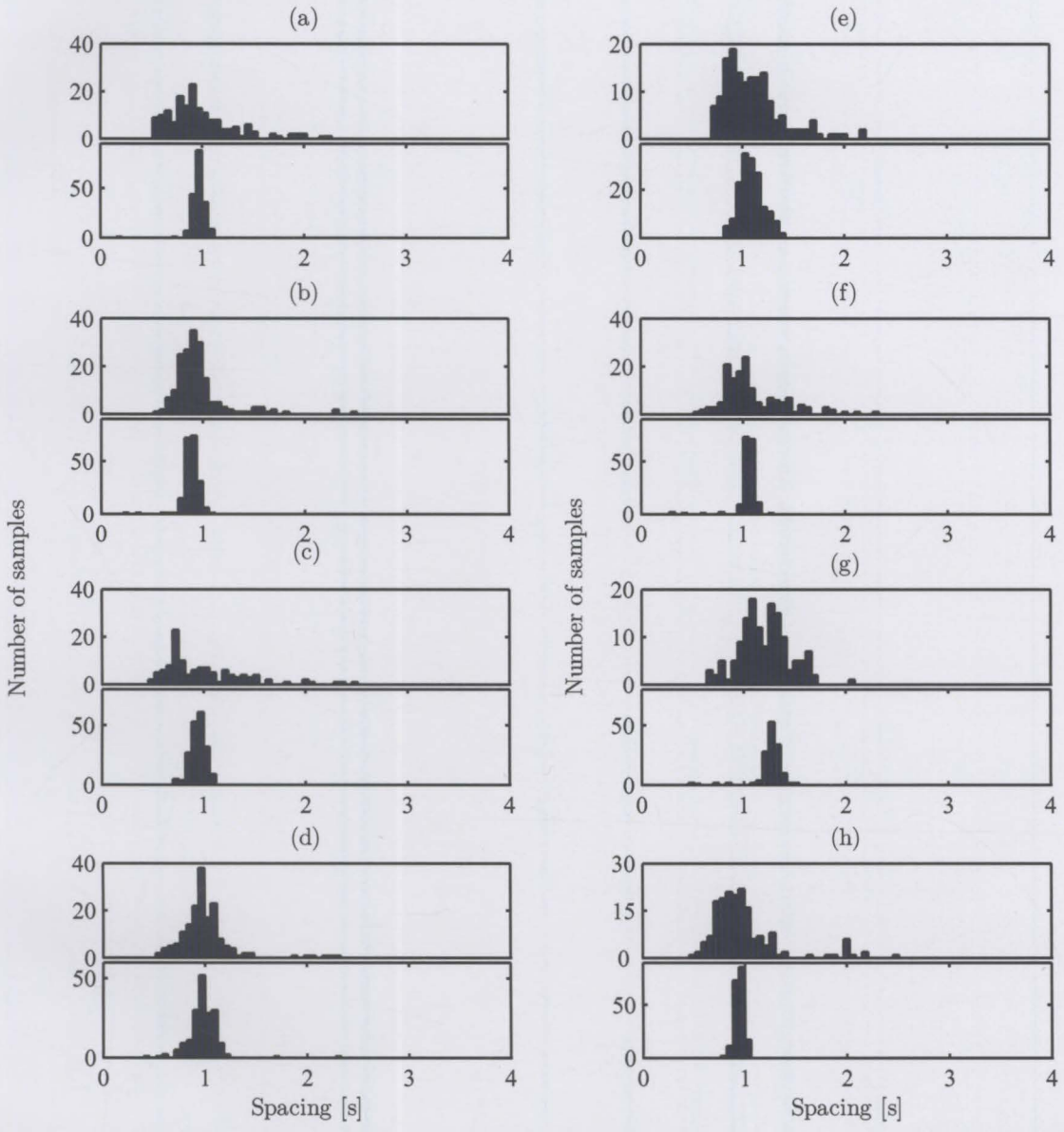


**Figure B.4:** *The histogram plots for the seven subjects (Subjects 1-8) are shown after matched filtering and peak detection was performed. The top plot in each of the plots (a)-(h) is the histogram of the measured data while the bottom plot is the histogram of the ECG.*

heartbeat data). This observation is confirmed in Table B.2 where the variance values obtained for the subjects are larger than that obtained for the experiments with only heartbeat data. Other than the result for *Subject3*, the variance values for the subjects are still much smaller than that for brown and white noise. The result obtained for *Subject3* indicates that the developed heartbeat detection system did not work well for this particular subject. Only 117 heartbeats out of the 191 were detected. After investigation it was found that the data was of poor quality, due to many artefacts due to movement by the subject. Except for the increase in width of the histogram peaks, the position of the

**Table B.2:** *Results of statistical analysis for ECG and PESD data using PESD data that contains both respiration and heartbeat.*

| Data sets | ECG data | | | PESD data | | | |
|---|---|---|---|---|---|---|---|
| | Mean | Med | Beats | Mean | Med | Var | Beats |
| Brown noise | N/A | N/A | N/A | 55.82 | 61.22 | 0.181 | 145 |
| White noise | N/A | N/A | N/A | 64.93 | 75.47 | 0.167 | 182 |
| Subject1 | 62.37 | 67.50 | 186 | 60.63 | 65.93 | 0.119 | 167 |
| Subject2 | 68.28 | 68.18 | 204 | 61.90 | 65.93 | 0.079 | 183 |
| Subject3 | 63.88 | 63.83 | 191 | 59.82 | 66.67 | 0.167 | 117 |
| Subject4 | 61.13 | 61.22 | 182 | 59.66 | 61.86 | 0.074 | 170 |
| Subject5 | 54.90 | 55.56 | 164 | 54.13 | 56.60 | 0.085 | 153 |
| Subject6 | 57.30 | 56.60 | 171 | 54.61 | 58.82 | 0.098 | 152 |
| Subject7 | 47.80 | 46.88 | 142 | 49.65 | 50.42 | 0.059 | 142 |
| Subject8 | 63.59 | 63.83 | 189 | 60.46 | 65.93 | 0.120 | 172 |

peaks on the x-axis are still similar. This suggests that the average measured heart rate for the entire duration of the recording is still accurate even with many heartbeats not detected. This can be seen in Table B.2 when comparing the median values for the ECG and PESD data.

The heart rates for the eight subjects are shown in Figure B.5 and Figure B.6 for using median and mean consecutively, to calculate the heart rate. Each point on the plot corresponds to the heart rate calculated for one window of data.

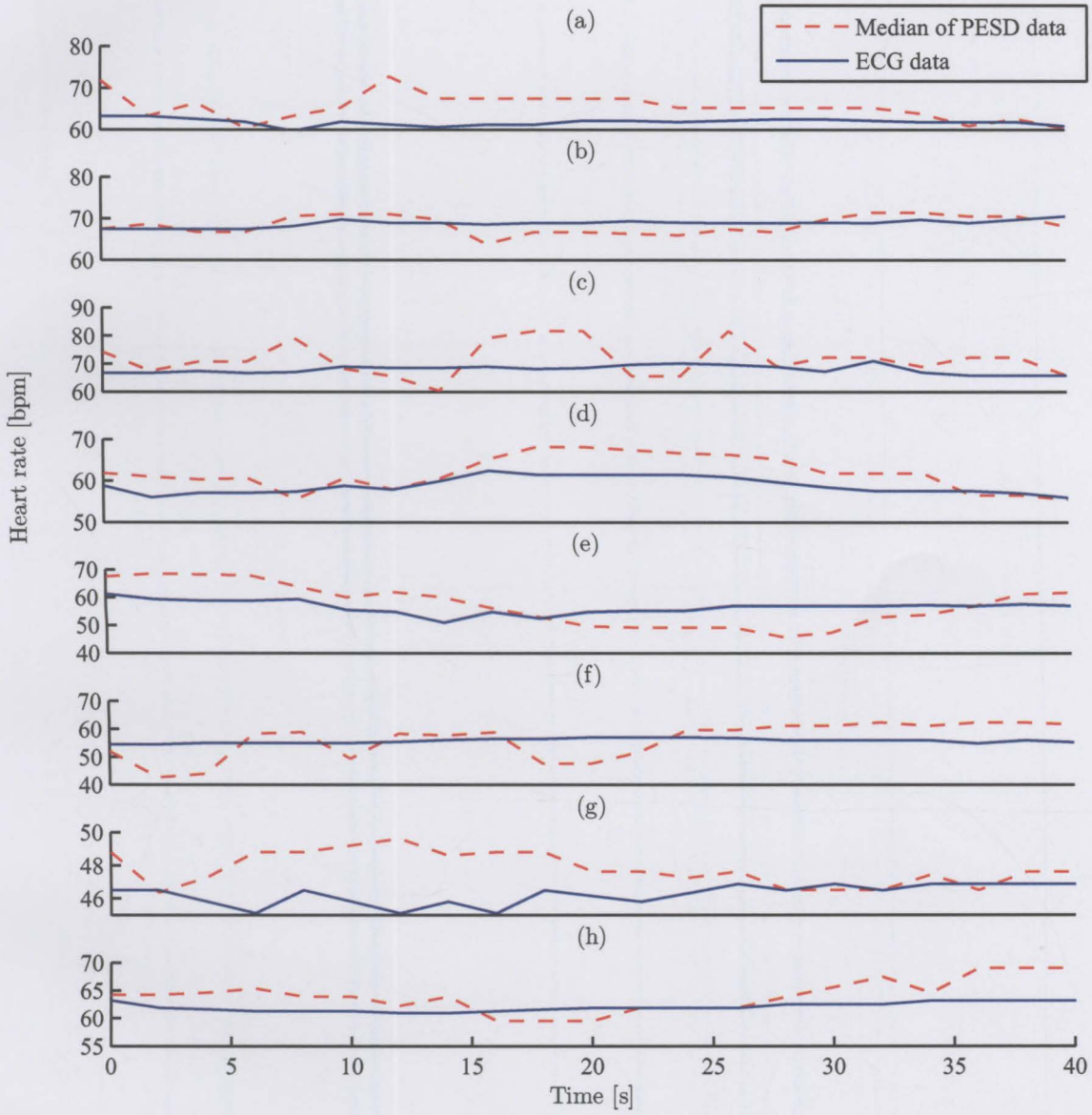


**Figure B.5:** *Plots (a)-(h) shows the heart rates for the eight subjects (Subjects 1-8) as calculated using the median of the data for the ECG versus the heart rate as calculated the measured PESD data.*

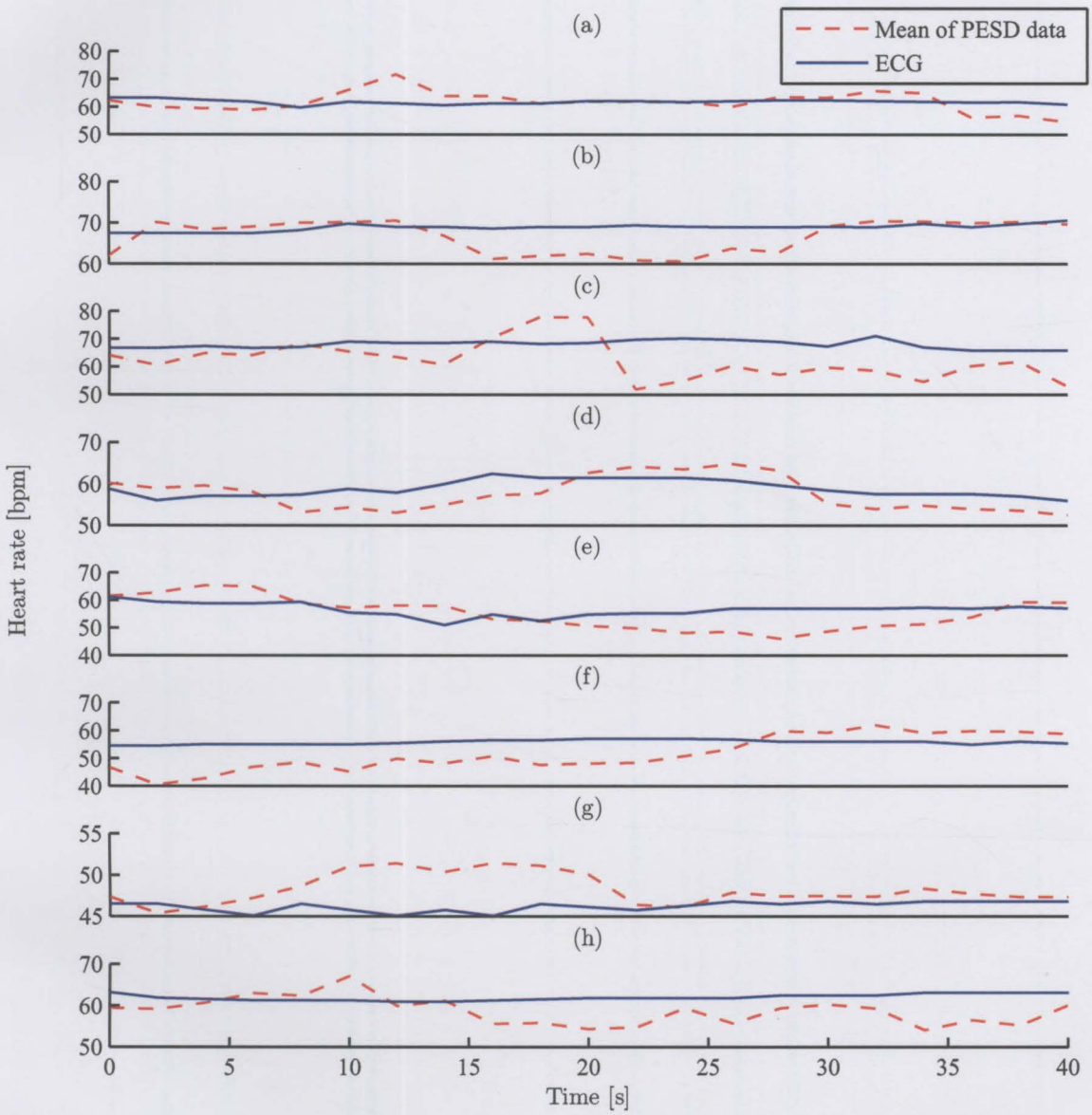


**Figure B.6:** *Plots (a)-(h) shows the heart rates for the eight subjects (Subjects 1-8) as calculated using the mean of the data for the ECG versus the heart rate as calculated the measured PESD data.*

**Table B.3:** *Results of statistical analysis for ECG and PESD data using infant PESD data that contains both respiration and heartbeat.*

| Data sets | ECG data | | | PESD data | | | |
|---|---|---|---|---|---|---|---|
| | Mean | Med | Beats | Mean | Med | Var | Beats |
| Brown noise | N/A | N/A | N/A | 55.82 | 61.22 | 0.181 | 145 |
| White noise | N/A | N/A | N/A | 64.93 | 75.47 | 0.167 | 184 |
| Subject1-1 | 67.722 | 68.182 | 67 | 62.690 | 70.588 | 0.123 | 48 |
| Subject1-2 | 68.800 | 68.182 | 67 | 62.275 | 69.767 | 0.105 | 52 |
| Subject1-3 | 69.153 | 68.182 | 68 | 50.445 | 54.299 | 0.106 | 34 |
| Subject1-4 | 68.577 | 68.182 | 67 | 59.980 | 70.588 | 0.099 | 30 |
| Subject1-5 | 69.153 | 69.364 | 68 | 59.754 | 65.934 | 0.088 | 51 |
| Subject2-1 | 69.589 | 75.472 | 68 | 59.031 | 67.416 | 0.099 | 53 |
| Subject2-2 | 69.815 | 73.171 | 68 | 55.803 | 61.538 | 0.088 | 46 |
| Subject3-1 | 70.659 | 70.175 | 70 | 50.065 | 55.556 | 0.083 | 45 |
| Subject3-2 | 71.174 | 69.767 | 70 | 51.191 | 54.545 | 0.119 | 48 |
| Subject3-3 | 70.146 | 68.966 | 69 | 54.174 | 54.054 | 0.059 | 49 |

## B.3 Infant data containing cardiovascular and respiratory information

By inspection of content presented in Table B.3 it is revealed that the accuracy of the heart rate detection with infants is much less than the accuracy obtained with the adult data. Both the mean and median calculated over the entire duration of the data sets shows this difference though the median produces much better results. The number of heartbeats detected from the PESD data is less than the actual number of heartbeats as counted using the ECG. The fact that all the data sets contains less beats in the PESD data compared to the ECG reference, suggests that a lower frequency is predominant in the matched filter output resulting in peaks being spaced further apart compared to the case when only heartbeats are present. This might be due to respiration artefacts and harmonics still being present in the signal. Also, the variance of the infant data is much larger with an average variance between all the data sets of $\sigma_X^2 = 0.105$. This value is still much less than the variance obtained when using only noise as input.